SURVEILLANCE PLAN FOR MONITORING
THE SHELF-LIFE OF
CHEMICAL DEFENSE COVERALLS

THESIS

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Presented to the Faculty of the Graduate School of Engineering

of the Air Force Institute of Technology

Air Education and Training Command

In Partial Fulfillment of the

Requirements for the Degree of

Master of Science in Operations Research

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March 1996

Acknowledgments

I would like to give my sincere thanks to my co-advisors, Maj Price Smith and Capt Edward Pohl. They gave me the right balance of letting me work on my own and giving me direction when I needed it. They challenged me and encouraged me every step of the way and actually made the thesis project enjoyable.

I would also like to thank my reader LtCol Stuart Kramer. He gave his valuable time and provided me with insights that improved the quality of the paper. I would also like to thank Mr. Curtis Fey from Human Resources at Brooks AFB. He was very helpful and always willing to give his time and knowledge on various aspects of the chemical defense coverall.

I also need to thank my wife, Deborah, and my three sons, Greg, Travis, and Timmy, for giving me the moral support and understanding when I couldn't spend as much time with them as I would have liked.

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Abstract

This thesis found a surveillance plan to be used to monitor the shelf-life of the Air Force's chemical defense coveralls. The sampling tests are destructive and the objective was to find a surveillance plan that would minimize the number of suits sampled yet provide enough information to accurately determine if the chemical defense coveralls had degraded past a minimum acceptable level.

Six sampling plans were developed and compared. The plans included the Air Force's original fixed sampling plan, several variations of sequential sampling plans, a Bayesian sampling plan, and an ad hoc pre-posturing plan.

Simulations were run with each plan under various degradation functions and various values for the test variables. It was determined that the truncated sequential plan showed the most promise for accurately predicting if a population of suits should be accepted or rejected using a minimal amount of suits.

SURVEILLANCE PLAN FOR MONITORING THE SHELF-LIFE OF CHEMICAL DEFENSE COVERALLS

1. Introduction

1.1 Statement of Problem

A cost effective surveillance plan is needed to monitor the shelf-life of chemical defense coveralls in the United States Air Force's inventory. The surveillance plan should detect deterioration in the reliability of the chemical defense coveralls and provide the decision makers with the knowledge and insight needed to determine the coveralls' shelf-life.

1.2 Background

The CWU-66/P is a chemical defense coverall worn as an outer garment by Air Force flight personnel for protection against chemical warfare. The suits currently have a projected shelf-life of ten years and cost approximately $375 each. The Air Force currently has 15,848 of these suits in inventory that were manufactured in 1990, and plans to purchase 40,000 more suits to be manufactured in fiscal year 1996. The Air Force also has 21,980 units of an older version of chemical defense coveralls in inventory. This suit, the CWU-77/P, was also manufactured in 1990. In addition to these suits, the Department of Defense plans to have a joint service chemical defense suit with the potential of one million suits to be manufactured and purchased by the four armed services.

The newly manufactured CWU-66/P will be manufactured in approximately 32 lots, with each lot containing an average of 1500 suits. Arrangements have been made with the manufacturer

to have 15 suits randomly pulled from each production lot. These suits will then be reserved for sampling. In addition, 60 suits each of the CWU-66/P and CWU-77/P will be pulled from existing inventory to be used for sampling. A graph of the current inventory and number of chemical defense coveralls set aside for sampling are shown in Figures 1 and 2. All suits that are pulled for sampling will be sent to Natick Research, Development, and Engineering Center for storage and testing.

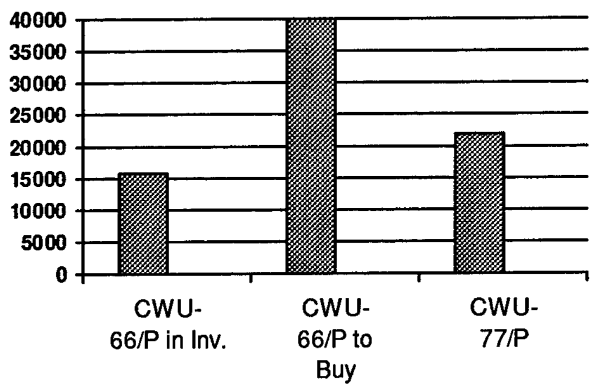


Figure 1. Inventory of Chem Suits

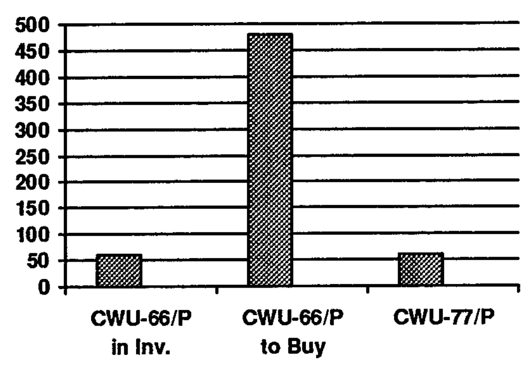


Figure 2. Chem Suits for Sampling

Cost of the testing will be approximately $625 per suit. The suits will be tested for simulant adsorption, breaking strength, tearing strength, seam strength, water adsorption and spray rating.

The testing also includes a visual inspection of the packaging to ensure that it is air and water tight, and an adhesion test, both of which are pass/fail visual tests.

The current sampling plan to be used by the Air Force follows the sampling plan developed by the Army to monitor their own chemical defense suits. This plan divides the total population of stored suits into three groups based on which lot they came from. Three suits from each lot will be tested in year zero. This will give a baseline for the test results in the later years to be compared to. The rest of the suits will be tested annually starting in year five, with samples being drawn from one of the three groups of suits. Using a rolling three year sampling plan, samples from each group will be tested every third year. Table 1 shows how each lot is placed in a group and what years the lots' samples will be tested.

Table 1. Lot Sampling Plan

Group	Lots	Years Tested
1	1,4,7,...,28,31	5th, 8th, 11th, 14th
2	2,5,8,...,29,32	6th, 9th, 12th, 15th
3	3,6,9,...,27,30	7th, 10th, 13th, 16th

The Army delegated the authority to Natick Research to decide whether to accept or reject a population of suits based upon the sampling results. The results of the individual tests on each suit will be available to the Air Force for their own analysis.

1.3 Scope

This research will attempt to extend the projected 10 year shelf-life and increase the overall reliability of the chemical defense coverall by focusing on the surveillance plan for its shelf-life. By minimizing the number of samples needed for a high degree of confidence in the reliability of the suit, money is saved in the sampling/testing cost. Sample size will be minimized by exploring

the use of Bayesian statistical techniques and sequential sampling. If the results of this sampling plan indicate the reliability of the suits exceed the projected 10 year shelf-life, then this will reduce the life cycle costs by extending the life of the suit.

In order to minimize the cost of the surveillance plan, this plan will take into consideration that the Air Force is the owner of the suits, and therefore, will take a loss from either a Type I or Type II error in the sampling. That is, if a population of suits is accepted when it should have been rejected, or rejected when it should have been accepted, the Air Force incurs a loss. In order to reduce the computational complexities, it is assumed that testing is 100% accurate. If we do not assume testing is 100% accurate, we would need to compute some type of probability distribution that would model the probabilities of how far the tests results are from the true values, and the calculations would become rather unwieldy for the scope of this thesis.

It is also assumed the suits will degrade over time. This research will look for a method to connect previous years' test data with the current year's testing in order to account for a degradation in the reliability. Degradation in the reliability of protective fabrics is known to be caused by oxidation and hydrolysis. The sponsor stores the suits that are to be sampled in an environmentally controlled warehouse, therefore, we cannot take into account the possibility that storage conditions may have an effect on the suits' reliability. The chemical suits are not stored under controlled conditions in the field. Future sampling plans may want to store the suits in varied conditions, i.e., hot, cold, humid, etc., or draw the suits randomly from the field and take into consideration how the storage conditions may effect the reliability of the suits.

This surveillance plan is intended to be a decision tool for the decision maker rather than a decision maker in its own right. That is, the surveillance plan is not intended to explicitly decide whether to reject or accept a population of suits. Rather it will be a tool for the decision maker to use to help him make a decision as to reject or accept a population of suits. The decision maker

will also take into account reliability thresholds, budgets, and the Air Force's own needs in his final decision.

1.4 Research Approach

In order to derive a high degree of confidence in the reliability of the suits with a small sample size, an approach other than fixed classical statistical sampling is needed. Bayesian statistical approaches and sequential sampling will be explored in order to increase confidence in the reliability of the suits while using small sample sizes. Bayesian statistics allows the use of prior data and expert knowledge in determining the reliability of the suits.

Many different approaches incorporate the use of Bayesian statistics and sequential sampling. These approaches will be examined and analyzed to determine which approaches will work best for the stated problem. Since data from the Army's tests on their chemical suits is available, one approach may be to incorporate this prior data into the Air Force's assessment of the chemical defense coverall's reliability. Another approach will be the use of sequential testing. Sequential testing allows the testing to be terminated earlier in the sampling if it is clear that the test results will result in accepting or rejecting a sample.

With the completion of a sampling model, computer simulation will be used to confirm that the surveillance methodology works. Various distributions will be used to model the reliability degradation of the suits in the simulation to measure the robustness of the proposed methodology. The simulation will ensure that the model detects reliability degradation within the producer's and consumer's risk thresholds that are given.

After all the sampling methodologies are developed and the output of the simulations are analyzed, a summary and recommendation will be made. We will recommend which sampling plan

appears to work best for sampling the chemical defense suits and conclude with comments that may help the decision maker in determining when to accept or reject a population of suits.

2. *Literature Review*

2.1 *Introduction*

This literature review considers current concepts used in sequential sampling and Bayesian attribute sampling plans that can be applied to develop a surveillance plan to monitor the shelf-life of chemical defense coveralls.

2.2 *Definition of Surveillance Testing*

AFOTECP 400-1, describes surveillance testing as the following:

> Surveillance testing generally requires that a number of preproduction or production systems be placed in actual or simulated field storage conditions. Periodically, selected samples of these assets are removed from storage and examined for degradation from original specifications. The surveillance program's value to the operational tester lies in the availability of similar system data upon which to base a comparability analysis when developing an early system reliability prediction. (AFOTECP 400-1, 1991:A2-4)

2.3 *Plan of Development*

This review first briefly introduces attribute and variable sampling followed by an introduction to the development and concept of Bayesian statistics. With sampling and Bayesian statistics introduced, concepts in the use of Bayesian statistics in attribute sampling follows.

Having a background of the concepts needed to understand the applications of Bayesian statistics in attribute sampling, methods are given for determining the prior distribution of the probability parameter p in a binomial distribution. This is followed by a review of the applied methodologies that are used in the application of Bayesian statistics to attribute sampling.

Midway through the thesis process, it was found that the test results would not be reported as attribute data, but as variable data. Therefore, we started to concentrate on variable sampling

plans. Sequential sampling using variable data is introduced with a sequential sampling plan given for normally distributed test items. The chapter will close with a look at other sampling methods that deal with the problem of small sample sizes and destructive testing.

2.4 Sampling

Montgomery states that the purpose of sampling is to sentence lots (accept or reject them), not to estimate lot quality (Montgomery, 1991:552). Sampling is not designed to estimate the reliability or quality of the lots. Rather, a decision is made whether to accept or reject the lot based upon the results of samples that are drawn from a lot and tested. Sheng and Fan note that there is no mathematical difference between using quality or reliability in terms of defining the unknown characteristic of the percentage of the lot that is good (Sheng and Fan, 1992:307). The remainder of this paper uses quality and reliability interchangeably.

In attribute sampling, the results of the tests on the items in a sample are recorded as either a success or failure. In the most basic attribute sampling plan, the single sampling plan, the decision to accept or reject a lot is based upon the results of only one sample. The producer and consumer, that is "the party submitting the product for acceptance and the party for whom the decision is made regarding acceptance or rejection" (Grant and Leavenworth, 1988:402), agree upon three numbers before any sampling is done. These three numbers are: N, the number of items in the lot from which the sample is to be drawn; n, the number of items to be randomly pulled from the lot; and c, the maximum number of failures allowed in the sample in order to accept the lot. These numbers are usually derived through classical statistics and as a minimum, are functions of: lot size, required confidence intervals, required quality of items, and the α and β risk, which are now defined.

The α risk is defined as the probability of rejecting a lot when the quality of the lot is acceptable, and the β risk is defined as the probability of accepting a lot when the quality of the lot is not acceptable. The α and β risks are also known as the producer's risk and consumer's risk respectively.

In variable sampling, the actual numerical value acquired in a sampling test is reported, as opposed to the pass/fail value given in attribute sampling. The probability distribution of the characteristic being tested is assumed to be known. There are many different variable sampling plans available. For variable sampling, the focus will be on sequential sampling plans. The two main advantages of variable sampling over attribute sampling is that variable data usually provides more information on the characteristic being sampled and variable sampling requires less samples to be drawn from a population in order to meet the α and β requirements.

2.5 Bayesian Statistics

Bayesian statistics allows the use of prior knowledge, either in the form of past data or subjective judgment from experts, to be used in reliability analysis. Classical statistics does not allow prior knowledge to be used, so in a sense, it is lost knowledge. Two important practical benefits are gained by using Bayesian statistics in reliability analysis. The first is the increased quality of the reliability analysis that results from an accurate assessment of the prior knowledge. The second is the reduction in sample size that usually occurs as a result of the use of the prior knowledge (Martz and Waller, 1982:173).

The disadvantages of Bayesian statistics are the subjective choices of the prior distribution and the parameters for the prior distribution. There are of course no mathematical formulas for subjective judgments, so the choice of a prior distribution that is subjectively but thoughtfully chosen is always open for argument and disagreement. Along with the choice of the prior

distribution is the subjective choice of what data the prior is based on. Often prior distributions are based upon data obtained from past tests on systems similar to the system for which the prior is being constructed. This leads again to disagreements on which systems can be assumed to be similar to the new system being modeled. Also, it usually cannot be shown or demonstrated that the prior distribution is really from a certain probability distribution function. The prior distribution is often chosen so that it is mathematically tractable.

Bayesian statistics is based on a theorem by the Reverend Thomas Bayes who presented it in the eighteenth century. The well-known theorem is known as Bayes theorem and is as follows:

$$Pr(A/B) = \frac{Pr(A \cap B)}{Pr(B)} \tag{1}$$

In Eq (1), both sides are multiplied by *Pr(B)* and the result is

$$Pr(A \cap B) = Pr(B)\,Pr(A/B) \tag{2}$$

Rewrite Eq (2) as

$$Pr(A \cap B) = Pr(A)\,Pr(B/A) \tag{3}$$

and replace the result of Eq (3) into Eq (1). The result is

$$Pr(A/B) = Pr(A)\frac{Pr(B/A)}{Pr(B)} \tag{4}$$

where *Pr(A)* is the prior probability of event *A* occurring before any information from *B* is obtained, and *Pr(A/B)* is the posterior probability of *A* given the information from *B* (Kapur and Lamberson, 1977:368).

Eq(4) is used to apply Bayes theorem to probability distributions. Let x have a probability density function (pdf) $f(x)$, dependent on a parameter θ. In classical statistics, θ is assumed to be an unknown constant, but in Bayesian statistics, θ is considered to be a random variable, and our belief in the value of θ is described by a pdf, say $h(\theta)$.

Assume a random sample of n items is drawn from a population whose distribution is the pdf $f(x)$, and let y be a function of this random sample. Then we have a conditional pdf $g(y/\theta)$ for y given θ. The joint pdf for y and θ is

$$f(\theta, y) = h(\theta)g(y/\theta) \tag{5}$$

and assuming θ is continuous

$$f_2(y) = \int_\theta h(\theta)g(y/\theta)d\theta \tag{6}$$

which is the marginal pdf for y. Then using Eq (4), the conditional pdf for θ given the information y can be written as

$$k(\theta/y) = \frac{h(\theta)g(y/\theta)}{f_2(y)}, \ f_2(y) > 0 \tag{7}$$

where

$k(\theta/y)$	=	posterior pdf of θ given y
$h(\theta)$	=	prior pdf of θ
$g(y/\theta)$	=	likelihood of y given the value of θ
$f_2(y)$	=	marginal pdf for y

$k(\theta / y)$ is now the updated pdf for θ given the new information y (Kapur and Lamberson, 1977:372). Many texts on Bayesian statistics refer to the prior pdf and posterior pdf simply as the prior and the posterior. This thesis will follow this convention.

In Eq (7), it is $h(\theta)$, the prior pdf, where most of the controversy of Bayesian statistics comes from. The prior pdf is often not objectively determined, but rather, subjectively determined. If the prior could be determined objectively, the rest of the Bayesian approach falls out mathematically and there would be little cause for controversy in the Bayesian approach. However, since we are using experts' educated opinions and prior sampling data that may or may not correspond nicely to our current sampling, this subjectivity will remain controversial.

2.6 Using Bayesian Statistics In Attribute Acceptance Sampling

The most important and controversial decision in the use of Bayesian statistics in attribute sampling is the choice of the prior distribution. Not only does it need to be decided what kind of distribution the prior pdf should take, but it also must be decided what values are to be assigned to the parameter(s) in the prior.

A common approach in choosing a pdf for the prior distribution is to choose a conjugate prior distribution for the given sampling distribution. A conjugate prior distribution is a distribution that causes the prior and posterior distributions to always be of the same family of distributions. In this thesis, the sampling distribution is the binomial distribution, and its conjugate prior distribution is the beta distribution. No matter how many times the Bayesian approach is used on the binomial sampling distribution with a beta prior, the posterior distribution will always be of the beta family. By using a conjugate prior, the resulting posterior distributions are always mathematically tractable, which leads to the criticism that the conjugate prior is chosen purely for its mathematical tractability.

While this criticism is true for those who those who blindly choose a conjugate solely for tractability, it has been shown that for the binomial sampling distribution, the beta family is the best choice for the prior distribution, in that it is robust to deviations from the beta distribution. Weiler shows that if one uses a beta prior distribution, when the true prior distribution is not from the beta family, that the impact is negligible in many practical applications (Weiler, 1965:335-347). Dyer shows that for three different conditions: 1), when there is no available prior estimate for p; 2), when there is only a point estimate for p; and 3), when there is an interval estimate for p, where p is the probability of success in the binomial distribution, the beta pdf is the best choice compared to three other distributions. Best in the sense that the posterior distribution resulting from using the beta prior is the most accurate and robust in all three given conditions (Dyer, 1984:2051-2083). Dyer compared the beta pdf to three other common distributions likely to be chosen as the prior. These three other distributions were the normal, negative log-gamma, and kummer distributions.

Although these two authors give good arguments for using a standard beta for a prior, Pham and Turkkan make the point that a general beta could be used as a prior instead. They argue that in practice, the reliability of an item is usually high and that the limits of the values for the reliability are usually known. For example, the reliability of the chem suits may be known to be $.75 < p < .99$, and by ignoring these bounds, important information is lost. The standard beta takes on all values in [0, 1], but the general beta is defined on the closed interval [$p1$, $p2$], where $0 \leq p_1 , p_2 \leq 1$.

Whereas the standard beta is a conjugate to the binomial distribution, the general beta is not. In their paper, Pham and Turkkan give attention to the sensitivity of the posterior distribution when using a standard beta prior distribution when the actual prior distribution is a general beta distribution (Pham and Turkkan, 1992: 310-316). Using a standard beta for the prior when a

general beta is more appropriate, they show the sensitivity of the posterior distribution is not all that extreme when using the wrong beta distribution. Considering the prior is often subjective anyway, there is no great loss in information when using a standard beta when the actual prior is a general beta.

But for whatever choice is made for the prior, the analyst must be able to give good reason and justification as to why the prior was chosen. Once a choice is made for the prior, a preposterior analysis is recommended by Martz and Waller (Martz and Waller, 1982:187). This procedure analyzes the prior distribution before any sample data is collected by noting its impact on contradictory and confirming hypothetical data. The procedure consists of four steps:

1. With the amount of sample data expected, make up a set of likely and unlikely sample data.
2. Using the proposed prior distribution and each set of hypothetical sample data, compute the posterior distribution using Bayes' theorem.
3. Study the posterior distributions noting if they seem reasonable with their respective hypothetical sample data.
4. If the posterior distributions seem reasonable, the proposed prior may be a valid candidate for use. If they are not reasonable, adjust the prior and go back to step 2.

This preposterior analysis will help in validating a proposed prior distribution before any sample data is collected.

As mentioned earlier, a strong justification of the prior distribution must be documented in order to have a credible Bayesian acceptance sampling analysis. Along with documentation on the choice of the prior and the previously given preposterior analysis, a clearly defined posterior distribution on the parameter(s) of interest and an analysis of the sensitivity of the Bayesian

inferences to the prior, ensures a well defined Bayesian acceptance sampling analysis (Martz and Waller, 1982:189). We now move on to methods that have been developed for constructing a prior distribution for the binomial sampling distribution.

2.7 Methods for Constructing a Prior Distribution

Having developed a foundation for Bayesian statistics in acceptance sampling, an examination and review of the applications currently used for constructing a prior is warranted. The most commonly used and easily understood applications will be reviewed first. The complexity of the applications will increase as they are introduced. Most of the applications will concentrate on a binomial sampling distribution with a beta prior.

2.7.1 Uniform Prior.

One of the simplest priors for the binomial sampling distribution is the uniform distribution. The uniform prior is a special case of the beta distribution. It is often used when the analyst does not have any prior information to construct a more informative prior. It essentially says that every value of p $(0 < p < 1)$, which is the probability of a successful test, has an equal chance of being true. The development of the prior is shown here for the reader who is not familiar with Bayesian statistics. The posterior distribution for a binomial sampling distribution with a uniform prior is derived as follows:

$h(p) = 1$ The pdf for the uniform(0,1) distribution.

$g(x \mid p) = \binom{n}{x} p^x (1-p)^{n-x}$ The binomial pdf of having x successes in n trials.

$$f_2(x) = \int_0^1 g(x \mid p) h(p) dp$$

$$= \int_0^1 \binom{n}{x} p^x (1-p)^{n-x} (1) dp \quad \text{The marginal pdf for } x.$$

Placing the above equations into Eq (7) the posterior is obtained:

$$k(p\,/\,x) = \frac{\binom{n}{x} p^x (1-p)^{n-x} (1)}{\int_0^1 \binom{n}{x} p^x (1-p)^{n-x} (1) dp} \tag{8}$$

$$= \frac{p^{(x+1)-1} (1-p)^{(n-x+1)-1}}{\int_0^1 p^{(x+1)-1} (1-p)^{(n-x+1)-1} dp} \qquad 0 < p < 1 \tag{9}$$

where

$$\int_0^1 p^{(x+1)-1} (1-p)^{(n-x+1)-1} dp = \frac{\Gamma(x+1)\Gamma(n-x+1)}{\Gamma(n+2)} \quad n \geq x \tag{10}$$

Substituting Eq (10) into Eq (9), $k(p\,/\,x)$ is a beta distribution with parameters $x+1$ and $n\text{-}x+1$, which can be written as $B(x+1, n\text{-}x+1)$, where x is the number of successful trials and n is the total number of trials. The expected value of this posterior is simply the expected value of the $B(x+1, n\text{-}x+1)$ which is $(x+1)\,/\,(n+2)$.

2.7.2 Expert's Subjective Prior.

In this method of defining a prior distribution, the analyst interviews an expert of the system to be sampled. The expert is defined as someone who is intimately familiar with the items to be sampled. The expert gives his educated, subjective estimation of the following values for p, the probability of a successful Bernoulli test from an item taken from a lot to be sampled:

The prior mean probability $P1$, where $P1 = E[P]$,

The prior 95th percentile $P2$, where $Pr(P > P2) = 0.05$,

The prior 5th percentile $P3$, where $Pr(P < P3) = 0.05$.

That is, before the sampling is performed, there is only a 5% chance that the value p will exceed $P2$ and only a 5% chance that the value of P will be less than $P3$ (Martz and Waller, 1982:236).

This method provides a means for translating information about percentiles and means into a beta prior distribution. By picking any combination of pairs of from $P1$, $P2$ or $P3$, the analyst is able to get unique values for the parameters x_0 and n_0 to be used in the beta prior distribution, $B(x_0 , n_0)$. The values are obtained from a table that was constructed using numerical methods. The table simply gives the unique beta distribution that corresponds to the pair of percentiles and mean given by the expert. The posterior distribution, given n trials with x successes, can then be constructed from Eq (7). With a prior distribution of $B(x_0 , n_0)$, the posterior distribution is then $B(x_0 + x, n_0 + n - x)$, where n is the number of trials and x is the number of successful trials.

2.7.3 Method of Moments.

The method of moments allows a beta prior to be formed based on previously observed sample data from similar past experiments on similar items. Assume a sequence of N sets of binomial sampling tests were run, where for each set of tests, there were x_j successes out of a sample size n_j, for $j = 1$ to N, and p_j unknown. Also assume that the sample sizes do not vary too greatly from test to test.

Martz and Waller show that the sample mean for the probability of a successful trial, $\overline{p_u}$, and second sample moment, m_u^2 , about the origin of the sequence $\hat{p}_1 \dots \hat{p}_N$ are defined as:

$$\overline{p_u} = \sum_{j=1}^{N} \frac{\hat{p}_j}{N} \qquad m_u^2 = \sum_{j=1}^{N} \frac{\hat{p}_j^2}{N} \tag{11}$$

where $\hat{p}_j$ is defined as x_j / n_j. By the use of the method of moments procedure (Mann, Schafer and Singpurwalla, 1974:46-55), equate the sample moments to their expected values, and solve for x_0 and n_0, the parameters for the beta prior. Using this method, x_0 and n_0 are found by solving the following equations:

$$\hat{n}_0 = \frac{N(\overline{P}_u - M_u^2)}{NM_u^2 - K\overline{P}_u - (N-K)\overline{P}_u^2}, \qquad K = \sum_{j=1}^{N} n_j^{-1} \tag{12}$$

and

$$\hat{x}_0 = \hat{n}_0 \overline{P}_u \tag{13}$$

In the case where the difference in the sample sizes of the tests are severe, weights are given to the sample moments (Martz and Waller, 1982:312-315).

2.7.4 Marginal Maximum Likelihood.

Like the method of moments just presented, the marginal maximum likelihood also allows a beta prior to be formed based on previously observed sample data from similar past experiments on similar items (Martz and Waller, 1982:316-318). This method finds the parameters of the beta prior by maximizing the marginal likelihood function. The marginal distribution of X_j, where $j=1..N$, is

$$f(x_j, x_0, n_0) = \frac{n_j!\,\Gamma(n_0)\Gamma(x_j + x_0)\Gamma(n_j + n_0 - x_j - x_0)}{x_j!(n_j - x_j)!\,\Gamma(n_j + n_0)\Gamma(x_0)\Gamma(n_0 - x_0)} \tag{14}$$

and the marginal likelihood is just the product of these, for $j = 1..N$. The marginal likelihood is then maximized by finding the appropriate values for x_0 and n_0. By taking the log of the likelihood and differentiating with respect to x_0 and n_0, the following equations are found:

$$\frac{\partial \ln L}{\partial x_0} = \sum_{j=1}^{N}\sum_{i=0}^{x_j-1}\left(\frac{1}{x_0+i}\right) - \sum_{j=1}^{N}\sum_{i=0}^{n_j-x_j-1}\left(\frac{1}{n_0-x_0+i}\right), \quad n_j > x_j \geq 1 \tag{15}$$

$$\frac{\partial \ln L}{\partial n_0} = \sum_{j=1}^{N}\sum_{i=0}^{n_j-x_j-1}\left(\frac{1}{n_0-x_0+i}\right) - \sum_{j=1}^{N}\sum_{i=0}^{n_j-1}\left(\frac{1}{n_0-+i}\right), \quad n_j > x_j \tag{16}$$

Note in Eq (15), if $x_j = 0$ or $x_j = n_j$, then the corresponding summation on i is defined to be zero.

Equating these equations to zero and solving simultaneously, the maximum likelihood estimates for x_0 and n_0 are obtained. These equations must be solved numerically, and starting values are taken from the method of moments estimates. x_0 and n_0 are then the parameter estimates for the beta prior.

2.7.5 Empirical Bayes Single Sampling Plans.

This method considers a Bayesian attribute sampling plan without explicitly defining a prior distribution (Martz, 1975:652-653). It derives its prior from past data from similar lots of items that were sampled.

Reasons to use the empirical methodology instead of the method of moments and the marginal maximum likelihood, is that the assumption of a prior is sometimes undesirable when the lot fraction defective is believed to be concentrated over a range much smaller than [0, 1] (Pham, 1990:7). Another reason for not explicitly defining a prior is that sometimes quality control personnel are reluctant to assume a specific prior that cannot be easily verified.

Consider m lots having been sampled, where for lots j = 1 to m, the following are defined. Note that before, p was defined as the fraction of the lot **not** defective. We will now uses q as the fraction **defective** in the lot:

q_j fraction **defective** in jth lot

N_j lot size of jth lot

n_j sample size of jth lot

x_j number of failures in jth sample

y_j $x_j \, / \, n_j$

$\underline{y}$ $(y_1 , y_2 ,\ldots, y_m)$

Martz develops a method to estimate the prior lot fraction defective density function $f(q)$, based upon a class of kernel estimators. $f(q)$ is given as the following:

$$f(q / y) = \frac{1}{(N)(h)} \sum_{j=1}^{m} k_j \left[\frac{q - y_j}{h} \right], \qquad 0 \le q \le 1 \tag{17}$$

where

$$h = h(m) = \begin{cases} W_{s_m} (\sum_{j=1}^{m} \delta_j)^{1/5} & s_m > 0 \\ 2(\sum_{j=1}^{m} \delta_i)^{1/5} \, / \, n_m & s_m = 0 \end{cases} \tag{18}$$

and

$$k_j(t) = \begin{cases} w_j n_j (1 - |t|) & \{|t| \le 1, y_j - h \ge 0, y_j + h \le 1\} \\ 2 w_j n_j h^2 (1 - |t|) / (2h^2 - (y_j - h)^2) & \{|t| \le 1, y_j - h \le 0\} \\ 2 w_j n_j h^2 (1 - |t|) / (2h^2 - (1 - y_j - h)^2) & \{|t| \le 1, y_j + h \ge 1\} \end{cases} \tag{19}$$

In Eq (18), $\delta_j = 1$ or 0 according to whether $w_j > 0$ or $w_j = 0$, respectively, and

$$s_m^2 = \sum w_j n_j (y_j - \bar{y})^2 \, / \, N \tag{20}$$

where

$$\bar{y} = \sum w_j n_j y_j \, / \, N \tag{21}$$

and

$$N = \sum w_j n_j \tag{22}$$

In this equation, w_j is a non-negative weight that is applied to the data from the jth lot. This weight is determined by the analyst, with the idea being recent lots should be weighted more heavily than distant past lots. Also weights of zero could be assigned to those lots that are not to be included in the computation of the prior. The constant W in Eq (18) should be set to 1 unless the prior is believed to have many local maxis and mins with sharp peaks. For the remainder of this methodology, W and w_j will be set to one.

By the use of Bayes theorem, Martz came up with a posterior probability for $Pr(Q \leq q \mid x)$. This equation is

$$Pr(Q \leq q \mid x, \underline{y}) = \begin{cases} \dfrac{\int_0^q f(x/q) f(q/\underline{y}) dq}{Pr(X = x/\underline{y})}, & \{Pr(X = x/\underline{y}) \neq 0\} \\ 0 & \{Pr(X = x/\underline{y}) = 0\} \end{cases} \tag{23}$$

where

$$Pr(X = x/\underline{y}) = \int_0^1 f(x/q) f(q/\underline{y}) dq \tag{24}$$

Martz develops the equations for the numerator and denominator for Eq (23), which are quite lengthy and complex.

Martz then tested his empirical Bayes sampling plan with the Bayes sampling plan where a beta prior distribution was assumed, by using Monte Carlo simulation. For unimodal symmetric or moderately skewed priors, the Empirical Bayes and beta-prior Bayes were in general agreement. For cases with highly skewed (such as U-shaped) priors however, the Empirical Bayes

methodology yielded an improvement over the beta-prior Bayes method. "The results of the test indicated that the Empirical Bayes estimators quite satisfactorily approximated the corresponding Bayes estimators" (Martz, 1975:657).

Martz shows how to find the optimal single-sampling plan using Empirical Bayes that attains the specified posterior consumer's and posterior producer's risks. He defines:

Posterior Consumer's Risk = $\beta(n, c) = Pr(Q > q_2 \,/\, \text{lot accepted}, \boldsymbol{y})$

Posterior Producer's Risk = $\alpha(n, c) = Pr(Q < q_1 \,/\, \text{lot rejected}, \boldsymbol{y})$

where q_2 is a value of q specified by the consumer that requires a high probability that Q does not exceed this value in accepted lots, and q_1 is a value of q specified by the producer that requires a low probability that Q does not exceed this value in rejected lots. Recall that Q is defined as the fraction **defective**. The sampling plan should then satisfy:

$$\beta(n, c) \leq \beta \quad (\beta \text{ Small})$$

$$\alpha(n, c) \leq \alpha \quad (\alpha \text{ Small})$$

where β and α are the maximum values of the specified risks declared by the consumer and producer. The optimal sampling plan will then be the plan that satisfies the two inequalities and has the smallest value of n. The methods of finding the optimal values of n and c are the same as those in Wood's method (Wood, 1983) that is presented later in this thesis.

Martz concludes that the Empirical Bayes method can be used to achieve specified posterior consumer and producer risks. In general the sample sizes under this Bayes method will be smaller than those in classical statistics, especially when the previous lots that were observed were of

excellent quality. The main advantage of Empirical Bayes is that the prior does not have to be explicitly assumed.

2.8 Bayesian Acceptance Sampling Plans for Binomial Distributions

This section reviews how Bayesian statistics are applied to acceptance sampling plans using attribute data. These two plans are based upon typical attribute acceptance plans, where the number of items sampled is minimized with respect to the constraints of the consumer's and producer's risks.

2.8.1 Bayesian Reliability Test Plans for One-Shot Devices.

This approach develops Bayesian attribute acceptance sampling plans for one-shot devices (Wood, 1983:1-18). A one-shot device is an item that is destroyed once it is used or tested. Examples of one-shot devices are missiles and bombs and in our case, can be extended to chemical protective coveralls. The plan uses data from similar testing attained previously to construct a prior. The previous test data will be referred to as $(N_0\ , k_0)$, where N_0 is the number of trials and k_0 is the number of **failures** that occurred.

Before any testing begins, the consumer and producer agree on the following values:

α_m = maximum tolerable value for producer's posterior risk

β_m = maximum tolerable value for consumer's posterior risk

r_α = reliability threshold for α calculation

r_β = reliability threshold for β calculation.

Once these values are agreed upon, they are used with the prior distribution to determine the sample size for testing (n_1) and to determine the maximum number of failures (M) allowed in order to accept the lot. After testing is completed, the actual values for the producer's and

consumer's risk, α and β, are calculated. In this methodology, α is defined as $Pr(r \geq r_{\alpha} / reject)$, and β is defined as $Pr(r \leq r_{\beta} / accept)$, where r is the actual reliability of the lot. Note that earlier articles referenced in this section used p rather than r as the reliability or probability an item would be successful.

Once the producer and consumer agree upon the values given above, the prior distribution is developed. This is accomplished by assuming there was a uniform prior distribution **before** the event (N_0 , k_0) took place. This uniform prior is then updated by the event (N_0 , k_0) in the usual Bayesian fashion and this new posterior is now the prior for the present testing. The uniform is a special case of the beta distribution, and so is conjugate to the binomial sampling distribution. More specifically, the prior is now a beta distribution with parameters $(N_0 - k_0 + 1, k_0 + 1)$, and every posterior and prior after this will be also be beta. Recall that in this method, k_0 represents the number of **failures**, not the number of successes.

The event (N_1 , k_1) is defined as the results of the new sampling test conducted. Also define M as the maximum number of failures allowed in the sample to accept the lot. The goal now is to find an equation for α, the actual producer's risk.

Recall

$$\alpha = Pr(r \geq r_{\alpha} / reject) = \int_{r_{\alpha}}^{1} f(r / reject) dr \tag{25}$$

and Bayes' Theorem, Eq (7), can be applied to show

$$f(r / reject) = \frac{Pr(reject / r) f(r)}{Pr(reject)} \tag{26}$$

where f(r) is just the prior distribution based on the data (N_0 , k_0), and $Pr(reject\,/\,r) = Pr(k_1 > M/r)$, is the probability that more than M failures occurred in the test with N_1 items tested. This latter term can be written using the binomial sampling distribution as

$$Pr(reject/r) = \sum_{k_1=M+1}^{N_1} \binom{N_1}{k_1} r^{N_1-k_1}(1-r)^{k_1} . \tag{27}$$

The denominator to Eq (26) is found by conditioning on r. That is

$$Pr(reject) = \int_0^1 Pr(reject/r)f(r) \tag{28}$$

and then substitute the prior distribution $f(r)$, which is a $B(N_0\text{-}k_0+1,\, k_0+1)$, and Eq (27) into Eq(28).

By substituting Eqs (27) and (28) and the prior $f(r)$ back into Eq (26) and integrating, the producer's risk can be found (Wood, 1983). The result is quite lengthy, but it is in closed form. It is a function of N_0 , k_0 , r_α , N_1 , k_1 , and M. It is found that the producer's risk is an increasing function of N_1 and a decreasing function of M.

The computation of the consumer's risk β is accomplished in the same way as the producer's risk. Where we can write

$$\beta = Pr(r \le r_\beta/accept) = \int_0^{r_\beta} f(r/accept)dr = \int_0^{r_\beta} \frac{Pr(accept/r)f(r)}{Pr(accept)} \tag{29}$$

By calculating this, it turns out that β is a function of N_0 , k_0 , r_β , N_1 , k_1 , and M, with β being a decreasing function of N_1 and an increasing function of M.

Now with the actual risks α and β defined, the number of samples and maximum failures allowed for acceptance, N_1 and M respectively, are solved such that $\alpha \leq \alpha_m$ and $\beta \leq \beta_m$. The algorithm to solve for N_1 and M starts by setting $M = 0$ and increasing N_1 (to reduce value of β) until $\beta \leq \beta_m$. Now at this point (N_1, M), it is determined if $\alpha \leq \alpha_m$. If $\alpha \leq \alpha_m$, then (N_1, M) is the solution. Otherwise, M is increased (to reduce value of α) until $\alpha \leq \alpha_m$ and then the algorithm is started over. This iterative scheme will result in the smallest N_1 with the smallest M, such that $\alpha \leq \alpha_m$ and $\beta \leq \beta_m$.

The sampling plan is then to take a sample of size N_1 and accept the lot if the number of failures $k_1 \leq M$ and reject the lot if $k_1 > M$. Once testing is accomplished and k_1 is known, the actual risks can be determined and a new prior can be updated for the next round of sampling if needed.

2.8.2 Combined Bayesian, Sample Theoretic Approach.

Launer and Singpurwalla give a Bayesian approach that is used to monitor the decay in the reliability of an arsenal (Launer and Singpurwalla, 1986). The method works on the premise that testing is expensive and destructive, so there is a strong desire to minimize the sample size.

Since reliability changes over time, sampling is done on a time-interval basis, i.e., annually. They define: n_t, to be the number of items to be tested in time period t; x_t, the number of items tested successfully in time t; and p_t, the probability the item tested in time t results in a success. The results are given as pass / failure, so we use a binomial distribution. p_t is a random variable given a prior density function, $g(p)$, and n_t is a decision variable that needs to be minimized. The equations used to solve for n_t are derived as follows.

When p_t is large, intuitively the number of failures in a sample of size n_t would be expected to be small. Given n_t and p_t, let x_t^* be the largest integer such that the chance of observing x_t^* or fewer successes is small, say α. Then we have

$$Pr\{x_t^* \text{ or fewer successes in } n_t \text{ tests} \mid p_t\} = \sum_{j=0}^{x_t^*} \binom{n_t}{j} p_t^j (1 - p_t)^{n_t - j} \leq \alpha . \tag{30}$$

Then if p_t changes to $p_t - \Delta$, with Δ large, then intuitively, the number of failures in a sample would be large, and if Δ is small, the number of failures in a sample would still tend to be small. A change of Δ should be detected with probability π, where Δ and π are determined by the decision makers. Let the consumers risk $B = 1 - \pi$, then

$$Pr\{x_t^* \text{ or fewer successes in } n_t \text{ tests} \mid p_t - \Delta\}$$

$$= \sum_{j=0}^{x_t^*} \binom{n_t}{j} (p_t - \Delta)^j (1 - p_t + \Delta)^{n_t - j} \geq 1 - B \tag{31}$$

In Eqs (30) and (31), p_t, α, B, and Δ are known, and n_t and x_t^* need to be obtained by solving Eqs (30) and (31) simultaneously. Eq (30) is then used to determine if the reliability of the items being sampled at time t is still p_t, with a Type I error α. If $x_t > x_t^*$, we assume the reliability of the items has not changed.

Since we do not know the value of p_t, a prior distribution is assigned to it as mentioned previously. Since p_t is a random variable with a distribution $g(p_t)$, Eqs (30) and (31) must be conditioned on p_t. These equations then become

$$\int_0^1 \sum_{j=0}^{x_t^*} \binom{n_t}{j} p_t^j (1 - p_t)^{n_t - j} g(p_t) dp_t \leq \alpha \tag{32}$$

and

$$\int_0^1 \sum_{j=0}^{x_t^*} \binom{n_t}{j} (p_t - \Delta)^j (1 - p_t + \Delta)^{n_t - j} g(p_t) dp_t \geq 1 - B \tag{33}$$

where these equations need to be solved simultaneously to obtain n_t and x_t*.

To implement this procedure, we define a prior distribution and then sample a population of items. If the sample indicates the population's reliability did not decay, (i.e. $x_t > x_t$*) the prior is updated with the sample results. If the sample indicates that the population's reliability did decay (i.e. $x_t \leq x_t$*), then the population is rejected.

As an alternative approach, it is suggested to replace p_t in Eqs (30) and (31) by the modal value of $g(p_t)$. The modal value is the most likely value of p_t, a single number. This would make the calculations easier and the number of items to be sampled would be less, since all the probabilities are concentrated on a single value. The paper does not give any indication though, as to the sensitivity of replacing the prior distribution of p_t by its modal value.

In a paper prior to this one, a sequential sampling technique is introduced by the same authors that uses the same equations (Singpurwalla and Launer, 1984:1-17). However this time, testing is done one item at a time and after each item is tested, it is determined whether to accept or reject the population, or continue testing more items. The maximum number of items tested would be no larger than n_t determined by solving Eqs (32) and (33). With this sequential sampling scheme, the expected number of items to be tested $E[n_t \mid p_t]$ can be determined.

Given n_t and x_t*, the probability that $n_t = x$ is determined by

$$Pr(n_t = x/p_t) = \begin{cases} \binom{x-1}{n_t - x_t^* - 1}(1-p_t)^{n_t - x_t^*} p_t^{x-(n_t - x_t^*)}, n_t - x_t^* \le x \le x_t^* \\ \binom{x-1}{n_t - x_t^* - 1}(1-p_t)^{n_t - x_t^*} p_t^{x-(n_t - x_t^*)} + \\ \binom{x-1}{x - x_t^* - 1}(1-p_t)^{x - x_t^* - 1} p_t^{x_t^* + 1}, x_t^* < x \le n_t. \end{cases} \tag{34}$$

Again, p_t is replaced by the prior distribution $g(p_t)$ which is $\beta(\gamma, \delta)$, and integrated with respect to p_t to obtain

$$Pr(n_t = x) = \begin{cases} \binom{x-1}{n_t - x_t^* - 1}\frac{\Gamma(\gamma+\delta)}{\Gamma(\gamma)\Gamma(\delta)}\frac{\Gamma(x - n_t + x_t^* + \gamma)\Gamma(n_t - x_t^* + \delta)}{\Gamma(\gamma+\delta+x)}, & n_t - x_t^* \le x \le x_t^* \\ \binom{x-1}{n_t - x_t^* - 1}\frac{\Gamma(\gamma+\delta)}{\Gamma(\gamma)\Gamma(\delta)}\frac{\Gamma(x - n_t + x_t^* + \gamma)\Gamma(n_t - x_t^* + \delta)}{\Gamma(\gamma+\delta+x)} + \\ \binom{x-1}{x - x_t^* - 1}\frac{\Gamma(\gamma+\delta)}{\Gamma(\gamma)\Gamma(\delta)}\frac{\Gamma(x_t^* + 1 + \gamma)\Gamma(x - x_t^* - 1 + \delta)}{\Gamma(\gamma+\delta+x)}, & x_t^* < x \le n_t. \end{cases} \tag{35}$$

Then $E[n_t]$ can easily be determined by summing $Pr(n_t = x)(x)$ for all values of x from $x = x_t^* + 1$ to $x = n_t$. .

Provided that those testing the samples have the capability of testing sequentially, a savings in the number of items tested is recognized.

2.9 Sequential Sampling.

Whereas the Bayesian methods dealt with attribute sampling, the Sequential methods will deal with variable sampling. As mentioned at the beginning of this chapter, it was discovered halfway throughout the thesis project that we would be given variable data rather than attribute data.

In sequential sampling, the sample size is not fixed as in single sampling plans, but rather it is a random variable. Sequential sampling allows the possibility of a reduced sample without the consumer's or producer's risks increasing. This is accomplished by testing one unit from a sample

at a time, and immediately determining if enough information is available to either accept or reject a population. After a test of an item, one of three possible actions may occur: (1) there is enough information to accept the lot; (2) there is enough information to reject the lot; or (3) continue the testing since enough information has not been acquired to either accept or reject the lot.

With sequential sampling, the test will always terminate and will seldom use more sample units for testing than is required with single sampling methods. The expected number of units to be tested in sequential sampling, $E(N)$, will be smaller than the fixed sample size in single-sampling methods. Since it has been determined that we will have variable test data from the results of the sampling, we will focus on sequential sampling that uses variable data as opposed to attribute data. For a more complete coverage of sequential sampling and the theory behind it, see (Mann, Schafer and Singpurwalla, 1974) or (Kapur and Lamberson, 1977).

2.9.1 Sequential Sampling from a Normal Distribution.

Assuming the variable test results of the chemical suits follow a normal distribution, a sequential sampling plan can easily be implemented. We will test the hypothesis that the true mean of the suits reliability U is greater than some value U_0. U_1 is defined as the value at which the analyst wishes only a β probability of erroneously accepting the test hypothesis when $U = U_1$. Using the conventional definitions of α and β, we come up with the following sequential sampling plan:

H_0: $U \geq U_0$ (Meets requirement)

H_1: $U < U_0$ (Does not meet requirement)

$$\text{Given } s = \frac{U_0 + U_1}{2} \tag{36}$$

$$1)\ Accept\ H_0 : U \geq U_0,\quad if \sum_{i=1}^{m} x_i \geq h_0 + ms \tag{37}$$

$$where\ h_0 = \frac{\sigma^2}{U_1 - U_0} ln \frac{\beta}{1-\alpha} \tag{38}$$

$$2)\ Reject\ H_0 : U \geq U_0,\quad if \sum_{i=1}^{m} x_i \leq h_1 + ms \tag{39}$$

$$where\ h_1 = \frac{\sigma^2}{U_1 - U_0} ln \frac{1-\beta}{\alpha} \tag{40}$$

$$3)\ \text{Take an additional observation if } h_1 + ms < \sum_{i=1}^{m} x_i < h_0 + ms \tag{41}$$

where m is the number of items sampled and x_i is the value of the ith sample (Mace, 1973: 132-135).

2.10 Other Approaches to Binomial Acceptance Sampling with Destructive Testing

While all of the above methods utilized Bayesian or sequential sampling methods in their approaches, two methods were found that dealt with small sample sizes and destructive testing that did not use Bayesian or sequential sampling. These two methods are given since they contain some ideas that may be utilized in the surveillance plan for the chemical defense suits.

2.10.1 Chain Sampling.

In Baker and Thomas's paper, chain sampling is used to develop an attribute acceptance sampling plan for expensive armor packages with destructive testing (Baker and Thomas, 1992:213-223). Chain sampling utilizes information over a series of lots. Instead of a single sampling plan with a sample of size n, where in this case, one failure results in the rejection of the lot, chain sampling utilizes information from the prior j lots. This method protects a lot from

rejection if a failure occurs in its sample, provided no failures have occurred in the immediately preceding j lots (Juran, 1988:25.37). In other words, if the prior j lots have no failures in their samples and a failure occurs in the present lot, it is not rejected as it would be under single sampling. It is particularly useful for small samples and protects lots from being rejected as a result of an anomaly of one bad item in a sample.

2.10.2 Methodology Using a Deteriorating Reliability Function.

Bain and Engelhardt developed an attribute sampling plan for one-shot devices with assumed deteriorating reliability (Bain and Engelhardt, 1991:304-311). The methodology does not use prior information, but does rely on the result of earlier samples as the sampling continues through time. The methodology also assumes a function $q(t)$ which is the probability that a device fails to work at time t, and samples are taken on a regular time interval, such as annually. Trials of items in the sample are pass / fail, and the methodology uses a binomial sampling distribution.

The methodology assumes a Weibull degradation function $q(t)$ where the shape parameter is assumed known, but the scale parameter is unknown. At time t_1, the first sample is drawn. Since no prior information is used, classical statistics are used for choosing the first sample size. It assumes no failures will be observed, so a sample size is found solving $b(0; n_1, q^*) = \alpha$, where $b(x; n, q)$ is the binomial pdf with parameters n and q, and α is the producer's risk. q^* is the maximum allowed probability for failure of items in the lot.

The next period's sample size is found solving for n_2 the following equation:

$$B(0; n_1, q(t_1))B(0; n_2, q^*) = \alpha \tag{42}$$

and solving for n_k in general for k independent samples from k periods

$$B(0;\, n_k\,,\, q^*)\prod_{j=1}^{k-1} B(0;n_j q(t_j\,))=\alpha \tag{43}$$

which is a recursive formula, resulting in less items sampled as the number of periods sampled increases.

The parameters of $q(t)$ are updated at each kth stage of testing, so that $q(t_k) = q^*$. The key factor in this methodology is finding a function that models the degradation of the reliability of the items being sampled.

2.11 Summary

In this literature review we gave a brief introduction to sampling and a review of Bayesian statistics for those not familiar with these two subjects. We then gave current methods for selecting a prior distribution for binomial sampling. Two Bayesian methodologies for sampling from a population with deteriorating reliability and destructive testing that utilized attribute data were given. This was followed by an introduction to sequential sampling and a method for sequential sampling using variable data assuming a normally distributed population. The literature review concluded with a couple of methodologies used to sample from populations where destructive testing was the only method for sampling.

3. Methodology

3.1 Introduction

This section introduces the methodology used in developing a sampling plan for the chemical defense coveralls. The first part of this section examines the assumptions made and current concepts held by the Human Systems Program Office at Brooks AFB. The second portion of this section is aimed at analyzing and evaluating the Air Force's current sampling plan for the chemical defense suits. Once a thorough understanding is gained from the current sampling plan, methodologies are developed to improve the current sampling plan and presented in the third part of this section. The last part of the methodology gives a description of the simulation methods used to compare the various methodologies introduced in this section.

3.2 Assumptions

The program managers at the Human Systems Program Office gave the requirement for a 95% confidence level for sampling. That is, their α value is .05. The program managers also indicated that they do not assume there will be any noticeable difference between lots and they assume the degradation of suits in different lots will occur at the same rate. Their current sampling plan is not designed to detect a degradation in performance of a single lot, but rather, it is designed to detect the degradation in the suits' protective capability as a whole population.

The Human Systems Program Office and Natick agreed to run a series of eight tests measuring eight different characteristics on each suit. These tests are given in Table 2. In our methodology, we did not include the Laundering test and the Packaging test, since these are simply observational pass/fail tests and the test managers did not feel they would be a factor in determining whether suits were passed or failed.. This left us with six tests. We further divided

three of the tests, Chemical Adsorption, Spray Rating, and Dynamic Adsorption, into two tests each since they involve laundered/unlaundered tests. Two of the tests, Breaking Strength and Tear Strength, are also divided into two tests each, since each test actually involves two tests, a warp test and a fill test. This further dividing of tests leaves us with a total of 11 tests.

Table 2. Surveillance Tests for Chemical Defense Coveralls

Characteristic	Requirement	Description
Packaging	N/A	Result of test is pass / failure
Chemical Adsorption	To be determined	Most important characteristic of suit. 2/3 of samples will be laundered, 1/3 not. 3 swatches sampled per coverall. Score for test is average of 3 swatches.
Breaking Strength	Minimum Values: Warp: 160 lbs Filling: 100 lbs	Test finds value at which material breaks. Warp value is strength of material running parallel with fiber, Filling is strength of material running perpendicular to fiber. 10 swatches sampled per coverall (5 per test). Score is average of 5 swatches.
Tearing Strength	Minimum Values: Warp: 6 lbs Filling: 4 lbs	Test finds value at which material tears. 2 swatches sampled per coverall, 1 for warp test and 1 for filling test.
Seam Strength	Minimum Value: 70 lbs	Tests strength of seams to breakage. 1 swatch per coverall.
Laundering Durability	N/A	Result of test is pass / failure. Tests how well material stands up to laundering.
Water Resistance - Spray Rating	Minimum values to be determined	Measures time it takes water to soak through material. 2/3 of suits tested are laundered, other 1/3 are not. 3 swatches per coverall. Score is average of 3 swatches.
Water Resistance - Dynamic Adsorption	Minimum Values to be determined	Measures amount of water material soaks up when immersed in water. 2/3 of suits tested are laundered, other 1/3 are not. 2 swatches per coverall. Score is average of 2 swatches.

With these tests we made the assumption that the test results are normally distributed. We feel this is an adequate approximation. In the past, the army has found that the results of their tests

on chemical suits usually center around a central mean with nearly equal amount of results falling above and below the mean. The army also ran a goodness-of-fit test on their chemical adsorption test data and the results indicated that a normal distribution was appropriate for modeling the data (Army Materiel Systems Analysis Activity memorandum, 1987). Assuming a normal distribution will allow us to use statistical methods that assume a normal distribution.

While each of the tests run on the suits have to meet minimum requirements, the program managers have not yet set statistical measures or criteria as when to say that a population of chemical suits is no longer effective. This is a judgment call made by the decision maker, that takes into consideration costs, age of suits, ability to replace existing suits, and which tests the suits have failed among other factors. For example, if the suits fail to meet the minimum requirement for the Chemical Adsorption test, this would tend to be more serious than if the suits failed to pass the Breaking Strength test. While we feel that the Chemical Adsorption test is the most critical test, the program managers at Aeronautical Systems Center were reluctant to commit to any type of weighting of the tests in terms of the tests relative importance in rejecting or accepting the suits. We will now take a look at the sampling plan proposed by the Human Systems Program Office.

3.3 Original Sampling Plan

As mentioned earlier, the Air Force has no statistical tests to help make a decision with its sampling plan, but instead makes a judgment call as to when a population of suits has degraded enough to reject. In order to compare their current sampling plan to proposed sampling plans, it is necessary to model the current sampling plan as a statistical test in which the measured characteristic of the suit is either rejected or accepted based upon the test results. Note that we are modeling **statistical** decisions to accept or reject based upon sampling results and comparing this

information to other sampling plans. We are not attempting to model the decision maker's decision process.

The first thing we did was to gather data from the Army's past tests on its chemical protective clothing. While it was pointed out by the testing analysts at Natick that the Army's suits and the Air Force's suits were made out of different materials, we felt the Army's data would be a good start. We used the Army's mean values and standard deviations of the test results. For the Seam Strength test, a test that the Army did not use on its suits, we set a hypothetical mean of 100 for the test and a standard deviation of 10. The minimum requirement for this test was set at a value of 70. We picked these values since they are reasonable values as far as the standard deviation being 10% of the mean and the minimum requirement for the test being 70% of the current mean value. These values are similar to what we have seen with the other tests.

We set up statistical tests for the 11 tests that would be run on the samples. We will run each of the eleven tests independent of each other. The hypothesis tests we used are defined as the following:

H_0: The mean value of a population's test parameter $\geq$ minimum requirement. (Meets the requirement).

H_a: The mean value of a population's test parameter < the minimum requirement. (Does not meet the requirement).

Note that in the case of Dynamic Adsorption, the actual requirement is a maximum requirement, while all of the other tests have minimum requirements, so the appropriate changes in the tests are made.

For the tests, the Human Systems Program Office set $\alpha = .05$ with no mention of any value for β. We decided to set $\beta = .10$, which is a reasonable choice. Recall that a Type II error is the

probability that a population is accepted, when in fact, the population should have been rejected. β is the probability that a Type II error will occur. The actual statistical test is a test that is found in most statistics books and is now presented. (Mendenhall, Wackerly, and Scheaffer, 1990: 434-455).

With a large sample size, the mean value of the results from the sampled tests will approach a normal distribution regardless of the distribution from which the sample is drawn. Some texts (Mendenhall, Wackerly, and Scheaffer, 1990: 319) state that 30 samples suffice as a large sample size, while most other texts say that it takes 100 samples to be regarded as a large enough sample. This property is from the widely known Central Limit Theorem. We will assume the results of the eleven tests can be modeled as normal distributions. Let U be the actual population average and U_0 be the minimum requirement for the results of a specific test. We run the following test:

H_0: $U = U_0$ (Meets requirement).

H_a: $U < U_0$ (Does not meet requirement).

Test statistic: $$T = \frac{\overline{Y} - U_0}{S / \sqrt{n}} \tag{44}$$

where S is the sample standard deviation or known standard deviation and n is the number of samples. $\overline{Y}$ is the average of the test results that have been sampled. The null hypothesis is then rejected if:

$$T < -t_{\alpha},$$

where the t-value has n-1 degrees of freedom. This statistical test was set up for all eleven tests of the samples with $\alpha = .05$. Solving the above inequality for $\overline{Y}$, the appropriate rejection regions (rr) are given in Table 3 for the values of $\overline{Y}$. If the value of $\overline{Y}$ falls below the reject region, the null hypothesis H_0 is rejected.

Table 3. Rejection Regions, Condition I

TEST	MEAN	STD DEV	MIN REQMNT	NUMBER OF SAMPLE	Reject Value
Break Strength (W)	246	27.22	190	30	181.8
Break Strength (F)	159.17	9.73	115	30	112.1
Tear Strength (W)	10.5	1.342	10	30	9.597
Tear Strength (F)	7.5	1.342	7	30	6.597
Seam Strength	100	10	70	30	67
Spray Rating	98.17	8.68	90		
(Laundered)				20	86.64
(Unlaundered)				10	84.97
Dynamic Adsorption	13.7	9.55	20 (MAX)		
(Laundered)				20	23.69
(Unlaundered)				10	25.54
Chemical Adsorption	2.32	0.29	1.3		
(Laundered)				20	1.188
(Unlaundered)				10	1.132

While these tests give Type I errors of .05, nothing is mentioned of Type II errors. Recall we wish to set $\beta = .10$. With Type II errors, it is only possible to calculate the actual β value at a fixed point. That is, at some fixed point below the minimum requirement of the tests, we want only a .10 probability of accepting a degraded population of suits. The fixed point U_1 was established for each test by simply taking 95% of the minimum requirement of the test. We are thus saying,

we would like only a .10 probability of accepting a suit when its test value has degraded to 95% of the minimum requirement.

In addition to these choices for U_0 and U_1, which we will call Condition I, we did a separate analysis where the starting means of the tests were chosen as U_0 and the minimum requirements for the tests were chosen as the values for U_1. We will call these values Condition II. The Condition II values give a higher value for the rejection region. These new values state that when we are at the starting mean value for one of the tested criteria of the suits, we want to accept the suits 95% of the time, but when the suits degrade to the minimum requirement, we want to reject the suits 90% of the time. Obviously, this puts a tighter requirement on the suits and we would expect to reject the suits earlier in their lifetime.

The actual value of β can be calculated by finding the probability that the $\bar{Y} \geq$ rejection region when the true mean of the tests $U = U_1$. This is accomplished by finding the probability that $t_\alpha \geq \frac{rr - U_1}{s / \sqrt{n}}$ where rr is the rejection region. This is found by finding this value on an inverse T-table, where t_α has n-1 degrees of freedom.

The most widely used way to obtain the needed β value if the actual β value is greater than desired is to increase the number of samples. Increasing the number of samples will always reduce the α and β risk. But since the samples are destructive and expensive, alternative ways to bring down the Type II error without drastically increasing the sample sizes are desired. We will now propose various sampling methods that will reduce the number of samples while maintaining the needed α and β requirements.

3.4 Pre-posturing Sampling

This method of sampling is very similar to the original method of sampling. The difference is instead of sampling 30 suits each year, fewer suits are sampled in the earlier years of the sampling plan and more suits sampled in the later years. Those suits that have been saved from sampling fewer suits in the earlier years are then used for sampling in the later years of the tests, so that more suits are tested as the suits are getting older. Over the period of 16 years of sampling, the total amount of suits sampled is the same as in the original sampling plan.

The idea behind testing fewer suits in the earlier years and more suits in the later years is that in the earlier years, the actual means of the suits' characteristic are probably far above that of the minimum requirement. Testing 30 suits in the first few years would be far in excess of the number of suits needed to meet the α and β probability demands. On the other hand, as the actual means of the suits' characteristics approach the minimum requirements, 30 suits is not enough to give a very small β value. By increasing the amount of suits tested at this time, the actual β value will decrease. Table 4 lists the number of suits to be tested each year with this methodology.

Table 4. Pre-Posturing Sample Plan

	YEAR											
	5	6	7	8	9	10	11	12	13	14	15	16
SUITS SAMPLED	12	12	21	21	30	30	39	39	48	48	30	30

The designed life of the chemical suits is ten years. Since the test managers are actually expecting a longer lifetime for the suits, the number of tests to be sampled increases after year ten. We assume we still have a finite value of 360 suits to be used as samples. The number of samples decrease in year 15 and 16 since the probability of the suits surviving this long may be a little optimistic. Potential test information would be wasted if we postured most of the suits to be sampled in years 15 and 16 and the suits were rejected in year 12. The success of this sampling

method relies on making an accurate prediction as to what year most of the suits' tested characteristics degrade to values exactly between U_0 and U_1, the values in which the most suits will be needed for testing.

3.5 Sequential Sampling

Sequential sampling allows the person running the tests to stop taking samples when a decision has been statistically made as to whether to accept or reject the testing of suits. Again, we are assuming the suits' test results are normally distributed. The sequential sampling for a normal population was presented in Chapter II. We will again assume that $\alpha = .05$ and $\beta = .10$ as we have in the two previous methodologies.

The sequential sampling concept is slightly similar to the pre-posturing method. When the actual means of the characteristics of the suits are far above the minimum, sequential sampling will allow for very few samples to be drawn. When the actual means are close to the minimum requirements, more samples are needed to ensure that α and β are less than or equal to .05 and .10 respectively. Each of the eleven tests are still treated independently of each other. A separate sequential sampling plan is used on each test. Figure 3 gives a graphical presentation of sequential sampling.

In Figure 3, the horizontal axis represents the number of samples taken and the vertical axis represents the sum of the results of the samples. The sum of the test results are plotted versus the number of samples. If the plots go into the Reject Region, the population is rejected and sampling ceases. If the plots go into the Accept Region, as indicated in this figure, the population is accepted and sampling ceases. As long as the plots remain between the Accept and Reject regions, sampling will continue. For our tests, we will assume that we can sample an infinite number of

suits, so we will run all sequential tests until we have made either an accept or reject decision for that particular characteristic.

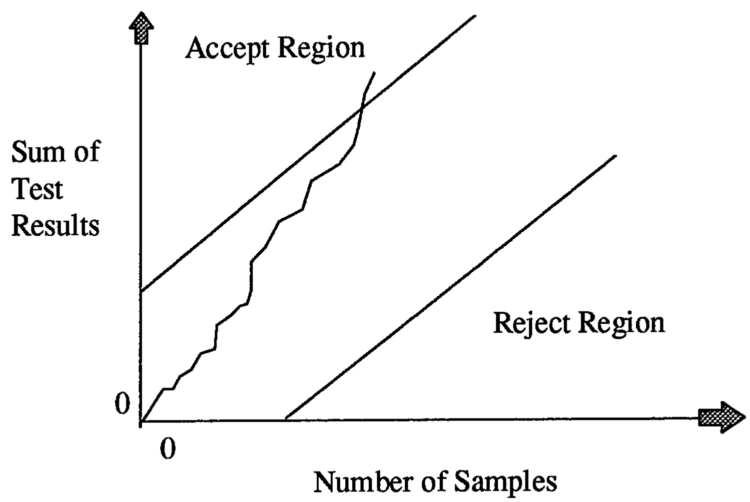


Figure 3. Sequential Sampling

3.6 Aggregated Sequential Sampling

One downfall of sequential sampling is that with eleven different tested characteristics, one of the tested characteristics may drive up the number of suits to be sampled while all other characteristics may be finished sampling after four or five suits. Since a whole suit must be destroyed for even one test, unbounded sequential sampling may not save that many suits in the long run. This problem is what drives this method of Aggregated Sequential Sampling.

This method of sequential sampling weights the values of the eleven tests so that the weights sum to one. The results of the eleven tests are then combined to form one test result. In this way, the decision maker can deem which measured characteristics are most important and assign these tested values the most weight.

The first step in this methodology is to standardize the tests' results. This is done by subtracting the minimum requirement from the actual test result, and then dividing this difference by the standard deviation for that particular test. By doing this we then have 11 normal distributions with standard deviations of one.

Each of these test results is then weighted so that the eleven weights sum to one. These eleven weighted standardized test results are then added together to form a single value. By adding these eleven weighted normal results together, the resulting distribution of these sums is still a normal distribution. The variance of this summed normal distribution can be found by taking the sums of the squares of the eleven weights (Law and Kelton, 1994:336).

To give some insight as to what the standardizing and weighting of the tests will do, we present an example. If all eleven test results were exactly at their minimum requirement, each individual standardized score would be zero. The sum of the weighted standardized values would also be zero, regardless of the choices for the weights. Now if ten of the eleven results were exactly at their minimum requirement but the one other result was slightly below its minimum requirement, then the sum of these weighted tests would be slightly less than zero. If the same were true that ten of the eleven test results were at the minimum requirement but the one other result was slightly above the minimum requirement, then the sum of the values would be slightly greater than zero. Therefore, if the sum of the weighted standardized results is greater than zero, we would want to accept the suit, and if the sum of the weighted standardized tests is less than zero, we would want to reject the suit. Our U_0 value for the aggregated test is then 0. That is, if the true mean of the sum of the weighted standardized test results is truly 0, we would want to accept the suits 95% of the time.

Intuitively, if a heavily-weighted test result was below the minimum requirement, it would take many other less-weighted test results above their minimum requirement in order to pass a suit.

In the same manner, if a less-weighted test result was below the minimum requirement, it would not have much effect in rejecting a suit due to its low weight.

The value for computing the type II error β is found by taking the value U_1 from each of the 11 tests (before standardizing) and finding its standardized value by standardizing this U_1 value using the method given above. For example, the suit criteria Seam Strength has a minimum requirement of 70, which is its U_0 value, and 95% of 70 is 66.5, which is the value for U_1. Its standard deviation is 10. Its standardized U_1 value can be computed as (66.5-70)/10 = -.35. See Figures 4 and 5 for a visual representation of the mean and U_0 and U_1 values for the Seam Strength test before and after the values were standardized.

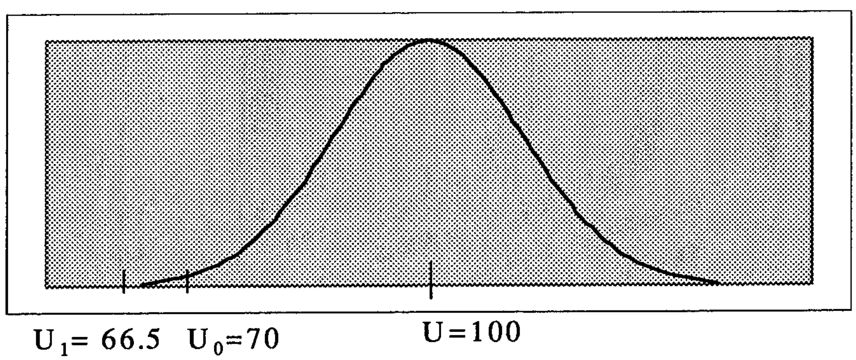


Figure 4. Seam Strength Values Before Standardizing

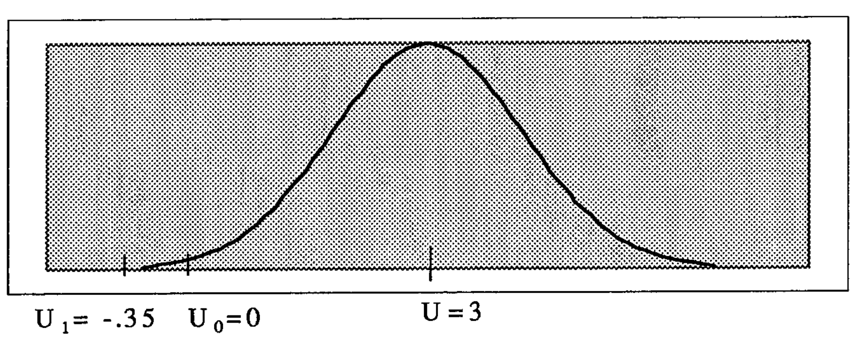
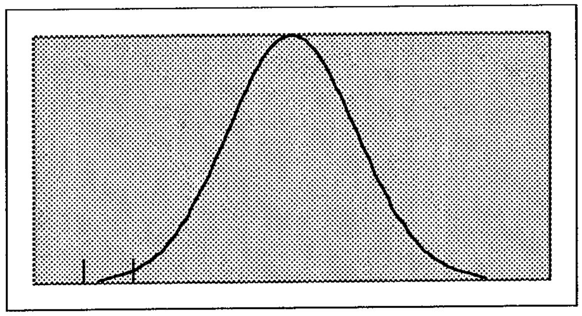


Figure 5. Seam Strength Values After Standardizing

These eleven standardized U_1 values are then multiplied by the respective weights given to the tests and summed. This summed value is then the U_1 value for computing the β error for the aggregated tests. That is, if all suits had degraded to 95% of their minimum requirement, we would want to accept the suits 10% of the time with $\beta = .10$. Note that when the results are standardized in this fashion, U_0, the minimum requirement for this Aggregated Sequential sampling technique will always be zero, and U_1 will be a negative value.

One note for the Dynamic Absorption test. Since this test has a maximum number as its test requirement, the value for its standardized normal is easily calculated by subtracting the actual test value from the maximum requirement rather than subtracting the requirement from the actual test value. The difference is still divided by the standard deviation and the result is then weighted and added with the rest of the tests in the given manner.

For our simulation, we weighted the laundered and unlaundered Chemical Adsorption test at .25 each and the other nine tests were weighted at .0556 each. This is because we feel Chemical Adsorption is the most important characteristic of the suits. These eleven test weights sum approximately to one. Using the above method for determining the aggregated U_1 value, we get $U_1 = -.2882$. Since $\beta = .10$, we want only a .10 probability of accepting the suits when sum of the standardized test results is -.2882. Obviously, the most heavily weighted tests have greater influence in whether a suit passes or fails. The sum of these eleven standardized tests have a normal distribution that has a standard deviation of .391, which is found by summing the squares of the eleven weights and taking the square root of the sum. See Figure 6 for a graph of the Aggregated test result values.



U_1= -.288 U_0=0

Figure 6. Aggregated Sequential Values

It is important to point out that this is the only methodology presented in this thesis that rejects or accepts the suits based upon the performance of all tested characteristics. In a sense, we are modeling the decision makers choice on what weights to give each test. In the other methodologies, we just find whether a suit's characteristic would be rejected or accepted based upon its respective test. In these other methodologies, the decision maker, taking into account the information from the different tests, would decide whether or not to reject the suit.

3.7 Truncated Sequential Sampling

Truncated Sequential Sampling is the same as the standard Sequential Sampling with the exception that a finite limit of suits is pre-determined before sampling is started. If an accept or reject decision is not attained by the time the suit limit is reached, a decision is made at this time to either accept or reject, even though the test may say to continue sampling. There are various methods to determine whether to accept or reject once the test limit has been reached. We simply divide the accept and reject region in half and whatever side the final test value is closer to, determines the decision to accept or reject the suits. See Figure 7 for a graphical representation of the truncated sequential plan.

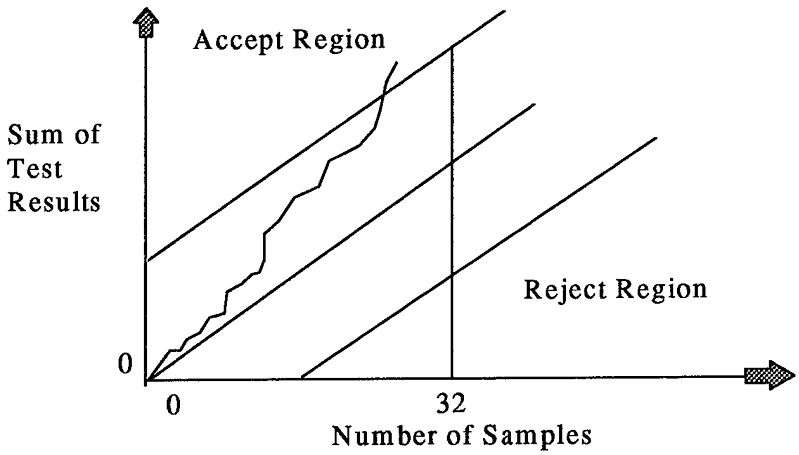


Figure 7. Truncated Sequential Plan

Note that in Figure 7, that if by 32 samples the plot of the sum of the test results versus the number of samples has not crossed into either the Reject or Accept Region, the population will be sentenced as determined by which side of the center line the plot falls on when 32 samples have been taken.

Our methodology will be as such. We start off in the first year of testing with 360 suits available at our disposal for testing. We will assume the suits will remain in service for the planned 16 years, thus we will sample suits each year from year 5 to 16, for a total of twelve years. This gives an average of 30 suits per year. So for the first year of testing, we will truncate testing at 30 suits. Our hope is that somewhat less than 30 suits will be sampled in the first year.

For example, say only 8 suits are tested in the first year. This then leaves us with 352 suits to be tested over the remaining eleven years. 352 divided by 11 now gives us 32 suits to be tested each year. This is how we will determine the maximum number of suits to be tested each year.

In running the sequential sampling for each of the eleven different tests, we will quit testing when either: 1) we reach our maximum suit limit for the year; or 2) when of all the tests have made a decision to either accept or reject before the maximum suit limit has been reached, whichever comes first. Even though a tested characteristic may have made an accept or reject

decision after only a few suits were sampled, we will still keep running the same tests as long as other tested characteristics still need samples to be tested in order to make a decision. This will allow more information to be gained on the actual values of the tested characteristics and every test will now have the same number of samples tested.

For our simulation of this methodology, we did not allow Dynamic Adsorption to determine if sampling should be continued. The reason for this is its variance is so large, that it always takes more than 30 samples to determine whether to accept or reject at our given α and β values. It may be possible to determine that the variance of the Dynamic Adsorption test is smaller than has been estimated by computing the sample variance after the baseline tests are run. For now however, we will assume that the variance will remain the same as the value we have assigned. If Dynamic Adsorption were included in the determination when to quit sampling, we would automatically be sampling 30 suits every year with no savings in suits in the earlier years.

3.8 Bayesian Sampling

This method uses the methodology of Launer and Singpurwalla's "A Bayesian, Sample Theoretic Approach" presented in the literature review, section 2.8.2. One small change is made to their approach. In their approach, they defined Δ to be a fixed constant so that the test always tries to detect a degradation of Δ in the reliability. In our method, Δ is always updated so that the test can detect a degradation in the reliability of the suits below a given value, this value being the minimum requirement of the tests. Δ is then decreasing as the reliability of the suits degrades. Δ is then the difference between the current estimated mean of the reliability and the minimum accepted value of reliability.

In this Bayesian Sampling method, the two parameters for the Beta distribution (we will call A and B) and Δ are chosen by the decision maker. α and β are defined as before at .05 and .10

respectively. The Bayesian algorithm, attempts to find the minimum number of tests needed in order to detect a degradation of Δ in the reliability of the suits while keeping α and β at their required values. The Beta distribution (Beta(A,B)) is the probability distribution of the parameter p_t, probability of a successful trial at time t, in the Binomial distribution. Recall that this Bayesian sampling plan and the Binomial distribution uses pass/fail criteria for their tests. Since this sampling plan uses attribute sampling, we need to convert the variable sampling results to attribute results. This can simply be done by regarding a test above the minimum requirement as a pass and a test below the minimum requirement as a fail.

The mean of the Beta(A,B) distribution is $A/(A+B)$. We can determine a beta prior distribution for the criteria being tested by finding the probability that the tested criteria will be above the minimum requirement for that particular test. We can do this given we know the tests' starting means, standard deviations, and minimum requirement values, again assuming a normal distribution.

For example, the Spray Rating test starts with a mean of 98.17, a standard deviation of 8.68, and a minimum requirement of 90. We want to know what is the probability we will get a test result of 90 or higher given we have a N(98.17,8.68) distribution. This is done by converting this Normal distribution to the Standard Normal distribution and looking up the value in a standard normal probability table. In this case, (90-98.17)/8.68 = .941. Looking this value up in a standard normal table, we find there is a .826 probability that the test will be above the minimum requirement. Figure 8 gives a visual representation of finding the probability that a Spray Rating result will be above the minimum requirement (90) when its true mean is 98.17. Values greater than 90 are considered a pass, values less than 90 are considered a fail. The area under the curve to the right of the minimum requirement is the probability that a result of the Spray Rating test will pass. This area is .826.

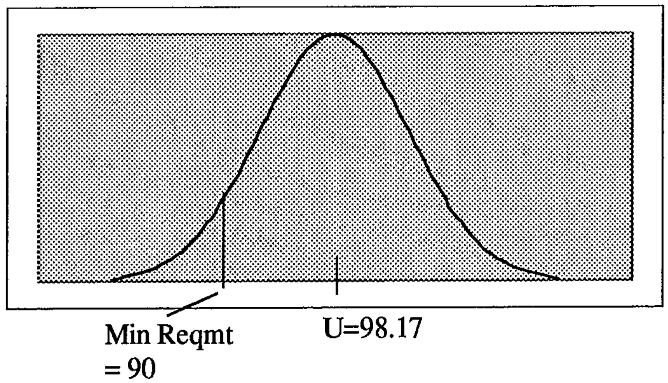
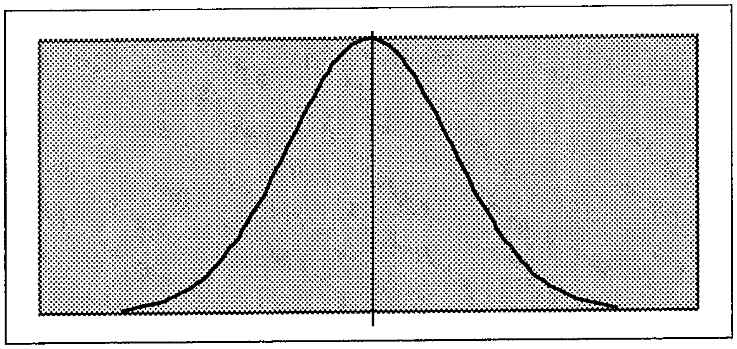


Figure 8. Spray Rating Probability of Passing Minimum Requirement

We now set $A/(A+B)$ equal to this probability of a test being above the minimum requirement and also setting $A+B$ equal to some value, say 10. In this way, the Beta(A,B) distribution starts out with a probability equal to the probability of a single test being greater than the minimum value. We equate $A+B = 10$ since this seems to be a reasonable value. As the sum of $A+B$ gets larger, the variance of the Beta distribution gets tighter and the prior distribution is given more weight in effecting the outcome of the accept or reject decision. On the other hand, as $A+B$ gets smaller, the variance for the Beta distribution becomes very wide and has little to no influence on the sampling. Further study will be needed in selecting the proper value for $A+B$.

The value for Δ is determined by the difference in the mean of the Beta(A,B) distribution and 0.5. This is because when the actual mean of a suit's measured test value is equal to the minimum required value for that test, it has a 0.5 chance of passing. This is due to the symmetry of the normal distribution and the fact that we regard a pass as a value being greater than the minimum requirement and a failure as a value less than the minimum requirement. In this way, we want to know when the degradation of the suits has fallen to less than a 0.5 probability of passing a test,

which indicates the mean value of the suits tested parameter is below the minimum requirement. See Figure 9 for a visual representation.



Min Reqmt
= True Mean

Figure 9. True Mean is the Minimum Requirement -- Values to Right Pass, Values to Left Fail

Table 5. Beta Parameters and Delta Values

TEST	PARAMETER A	PARAMETER B	Delta
BREAK STRENGTH (W)	9.8	0.2	0.48
BREAK STRENGTH (F)	9.9	0.1	0.49
TEAR STRENGTH (W)	6.4	3.6	0.14
TEAR STRENGTH (F)	6.4	3.6	0.14
SEAM STRENGTH	9.9	0.1	0.49
SPRAY RATING	8.3	1.7	0.33
DYNAMIC ADSORPTION	7.5	2.5	0.25
CHEMICAL ADSORPTION	9.9	0.1	0.49

In the case of the Spray Rating test, the test has a .826 probability of passing, so we set Δ equal to .326. We set Δ equal to .326 since .826 - .5 = .326. We want to know when the

reliability has degraded more than .326, (i.e., the suit would then have less than a .5 probability of passing the test) which indicates the reliability is below the minimum requirement. A table of the selected values for Δ and the A and B parameters of the Beta distribution for each test is given in Table 5.

The Beta parameter A is updated after every year of testing by adding A to the number of tests that pass. The beta parameter B is also updated each year by adding B to the number of failures in a particular test. The new estimated value of the probability of the suits ability to pass a certain test is then (A + *Passes*) / (A + *Passes* + B + *Fails*). This is a direct result of the Beta distribution being a natural conjugate for the Binomial sampling distribution as given in the literature review.

To find the number of tests that need to be conducted n_t, and the number of successes needed x_t, Launer and Singpurwalla show that the following inequalities must be solved.

$$\int_0^1 \sum_{j=0}^{x_t^*} \frac{n_t!}{j!(n_t - j)!} p_t^j (1 - p_t)^{n_t - j} g(p_t) dp_t \leq \alpha \tag{45}$$

and

$$\int_0^1 \sum_{j=0}^{x_t^*} \frac{n_t!}{j!(n_t - j)!} (p_t - \Delta)^j (1 - p_t + \Delta)^{n_t - j} g(p_t) dp_t \geq 1 - B \tag{46}$$

where $g(p_t)$ is the beta distribution.

Launer and Singpurwalla then show that these two inequalities can be rewritten as follows:

$$\frac{\Gamma(A+B)}{\Gamma(A)\Gamma(B)} \sum_{j=0}^{x_t} \binom{n_t}{j} \frac{\Gamma(j+A)\Gamma(n_t - j + B)}{\Gamma(n_t + A + B)} \leq \alpha \tag{47}$$

$$\frac{\Gamma(A+B)}{\Gamma(A)\Gamma(B)}\Delta^{n_t}\sum_{j=0}^{x_t}\binom{n_t}{j}\times$$

$$\left[\sum_{l=0}^{j}\binom{j}{l}\Delta^{-l}(-1)^{j-l}\left\{\sum_{m=0}^{n_t-j}\binom{n_t-j}{m}\Delta^{-m}\int_{\Delta}^{1}p_t^{\,l+B-1}(1-p_t)^{m+B-1}dp_t\right\}\right] \geq 1-B \tag{48}$$

They claimed that both of these inequalities are increasing functions of x_t but we proved this not to be true. Eq(47) is an increasing function of x_t, but Eq(48) is not. This is important because the algorithm they gave for solving these inequalities requires this property. The algorithm had to be modified slightly to achieve the correct answer. With the correct algorithm, the smallest values of n_t and x_t can be found that satisfy the above inequalities. The FORTRAN program for this algorithm and the accompanying simulation is given in the Appendix A.

3.9 Simulation

With all of the proposed sampling plans developed, we will run various simulations to help determine the ability of each sampling method to properly sentence a population of suits as either good or bad. The simulations are run in the simulation language SLAM II, except for the Truncated Sequential Sampling and Bayesian plan, which are run in FORTRAN. Pritsker gives a nice introduction to SLAM II for the interested reader (Pritsker, 1986).

To simulate the degradation of the characteristics of the suits, six different Weibull survival functions are used. The Weibull distribution was chosen since the shape of its survival function can be greatly varied. In the simulations, the variances are assumed to remain constant, while the means of the suits' characteristics decrease in proportion to the Weibull survival function. For example, if a characteristic of a population of suits starts out at time 0 with mean 100 and at $t = 6$ the value of the Weibull survival function was .88, then the population's mean at time $t = 6$ for that characteristic would be 88. Figure 10 gives a visual picture of the survival functions for the six

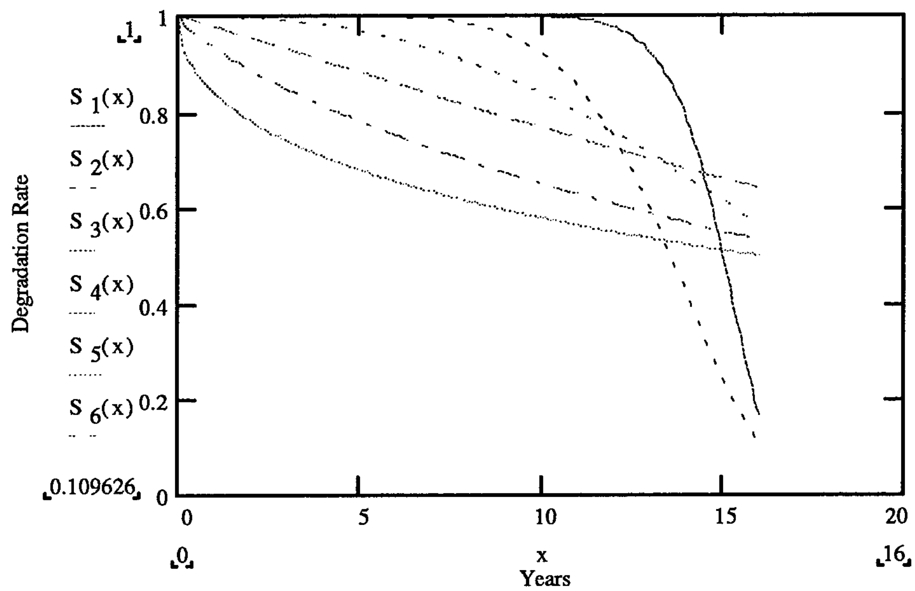


Figure 10. Degradation Graph of the Weibull Survival Functions

Table 6. Degradation Values from the Weibull Survival Functions

	DEG 1	DEG 2	DEG 3	DEG 4	DEG 5	DEG 6
YEAR 5	1	0.999	0.883	0.78	0.679	0.969
YEAR 6	1	0.998	0.859	0.751	0.654	0.952
YEAR 7	1	0.993	0.836	0.723	0.632	0.93
YEAR 8	1	0.983	0.812	0.697	0.613	0.904
YEAR 9	1	0.961	0.789	0.672	0.595	0.873
YEAR 10	0.998	0.921	0.766	0.649	0.578	0.838
YEAR 11	0.993	0.852	0.744	0.628	0.563	0.799
YEAR 12	0.976	0.744	0.723	0.607	0.549	0.757
YEAR 13	0.923	0.596	0.701	0.587	0.536	0.711
YEAR 14	0.784	0.42	0.68	0.568	0.523	0.664
YEAR 15	0.505	0.245	0.66	0.55	0.511	0.614
YEAR 16	0.165	0.11	0.64	0.533	0.5	0.564
WEIBULL PARAMETERS						
1ST PARAMETER	0.065	0.07	0.03	0.035	0.03	0.05
2ND PARAMETER	15	7	1.1	0.8	0.5	2.5

different Weibull functions used. Table 6 gives the values of the six Weibull functions for the twelve years that are tested, years through five through 16.

For each sampling plan that is developed, including the original sampling plan, the sampling plan is run 1000 times for each of the six weibull degradation functions. The exception to this is the Bayesian plan, which was only run 100 times each due to the extraordinary long simulation runs.

Each of the 1000 runs simulate all twelve years of the sample plans for all of the eleven tested characteristics given to a suit. As mentioned, each of the runs are also simulated across the six weibull degradation functions. Each run for the original sampling plan consists of sampling either 10, 20, or 30 normally distributed random numbers depending on which test is being given to a suit. Likewise, each run for a sequential sampling plan samples as many normally distributed random numbers as needed by the sequential plan.

The SLAM and FORTRAN programs can be seen in Appendix A. Having shown how our methodology has been constructed, we will now explore the data analysis of our simulation runs.

4. Data Analysis

4.1 Introduction

This chapter will examine the results obtained from using the methodologies introduced in Chapter 3. We will take a general view of the results and identify which methodologies warrant an in depth view of the data obtained from the simulations. A measure of effectiveness will be derived and applied to these methodologies. The results will then be compared between the various methodologies.

4.2 General View of Data

The spreadsheets that contain the simulation data and guidance for reading them can be found in Appendix B. One of the spreadsheets is displayed in Table 7. This particular spreadsheet displays the data obtained from simulating the Air Force's original sampling plan using the second degradation function and Condition I values. The number accepted values in the table represent the number of times that the population of suits were accepted for that particular characteristic out of 1000 simulations. The years in which the various characteristics of the suit first degrade below the minimum values are boxed in bold for easier viewing. One of the first things noticed when viewing the data, is that the different characteristics degrade to the minimum values at different rates. The reason for this is twofold. First, the starting means for the different characteristics start at various distances from their minimum values, and second, the standard deviations are different, which effect the rejection region. Since the characteristics degrade at different rates, some tests will reject the suits before other tests. Obviously, a nice quality one would want in a sampling methodology is its ability to accurately detect the degradation of characteristics in the same year that they fall below the minimum requirement.

Table 7. Simulation Spreadsheet, Original Sampling Plan, 2nd Degradation Function

AF Sample Plan I, Weibull (.07, 7)															
	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Break	190	246	**Mean**	245.8	245.5	244.3	241.8	236.4	226.6	209.6	183	146.6	103.3	60.27	27.06
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	565	0	0	0	0
Break	115	159.17	**Mean**	159	158.9	158.1	156.5	153	146.6	135.6	118.4	94.87	66.85	39	17.51
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	999	0	0	0	0
Tear	10	10.5	**Mean**	10.49	10.48	10.43	10.32	10.09	9.671	8.946	7.812	6.258	4.41	2.573	1.155
Strength (W)	9.597	1.342	**# Accepted**	1000	1000	1000	999	979	620	5	0	0	0	0	0
Tear	7	7.5	**Mean**	7.493	7.485	7.448	7.373	7.208	6.908	6.39	5.58	4.47	3.15	1.838	0.825
Strength (F)	6.597	1.342	**# Accepted**	999	1000	1000	1000	995	881	186	0	0	0	0	0
Seam	70	100	**Mean**	99.9	99.8	99.3	98.3	96.1	92.1	85.2	74.4	59.6	42	24.5	11
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0	0
Spray	90	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (UL)	84.966	8.68	**# Accepted**	1000	1000	1000	1000	1000	970	323	0	0	0	0	0
Spray	90	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (L)	86.64	8.68	**# Accepted**	1000	1000	1000	1000	1000	981	69	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	999	1000	989	908	699	440
Water (L)	20 (max)	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	23.69	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	999	999	983	836	448	149
Chem (UL)	1.3	2.32	**Mean**	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	997	44	0	0
Chem (L)	1.3	2.32	**Mean**	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.118	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	999	0	0	0

A point also needs to be made about differences between the simulations we labeled Condition I and those we labeled Condition II. Recall Condition I simulations are those where U_0 is equal to the minimum reject value and U_1 is equal to 95% of the reject value. Condition II simulations are those where U_0 is equal to the starting mean and U_1 is equal to the minimum reject value. As mentioned in Chapter 3, the noticeable difference between these two conditions of simulations is that Condition II simulations will reject suits earlier since it has a "higher standard" for accepting suits. But another difference that has significant effects on the Type I and II errors is the difference of the distances between U_0 and U_1. The difference in distances plays a significant role in determining how the suits will be accepted and rejected. In general, when the distance between U_0 and U_1 is large, it takes less samples to meet the α and β requirements. In general, we

can expect to see smaller Type I and II errors using Condition II simulations, since it is easier to distinguish if a population has a mean of U_0 or U_1. Table 8 shows the differences in the distances of U_0 and U_1.

Table 8. Distance Between U_0 and U_1

CONDITION	Break Strength (W)	Break Strength (F)	Tear Strength (W)	Tear Strength (F)	Seam Strength	Spray Rating	Dynam. Adsorp.	Chem. Adsorp.
I	9.5	5.75	.5	.35	3.5	4.5	1	.065
II	56	44.2	.5	.5	30	8.17	6.3	1.02

Most of the methodologies are accurate in rejecting suits when there is a sharp degradation. For instance in Table 9, the bold boxes in the spreadsheet indicate the first year in which a characteristic degraded below the minimum requirement. Since the degradation value drops relatively quickly in years 14, 15, and 16, note how few suits are accepted after a characteristic has degraded below the minimum requirement. On the opposing side, methodologies generally take a few years to reject a suit when the characteristic slowly degrades past the minimum requirement. An example of this is presented in Table 10. Again the bold boxes indicate the first year in which a characteristic degraded below the minimum requirement. Note that even a few years after a characteristic has degraded below the minimum requirement, the methodology still accepts many suits.

The reason that many suits are still accepted after the characteristics have degraded to the minimum requirement is that the test is set up so that at the minimum requirement U_0, 95% of the suits should still be accepted. As the suits' characteristics degrade further below the minimum requirement, a greater percentage of suits should be rejected. Many sampling methodologies contain another value, which we have called U_1, with the idea being that when the actual mean of the characteristic has degraded to U_1, we would like to accept the item being tested with a

probability of β. Figure 11 gives an example of an Operating Characteristic (O.C.) curve representing this idea. Calculations to obtain the O.C. curve can be found in many statistical books (Kapur and Lamberson, 1977). One of our main concerns with the Air Force's original sampling plan is that there is no mention β or a Type II error. We will now look at the data from simulating various methodologies and observe how well they did.

Table 9. Example of Sharp Degradation

AF Sample Plan I, Weibull (.065,15)															
	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	1	1	1	1	1	0.998	0.993	0.976	0.923	0.784	0.505	0.165
Break	190	246	**Mean**	246	246	246	246	246	245.5	244.3	240.1	227.1	192.9	124.2	40.59
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	989	0	0
Break	115	159.17	**Mean**	159.2	159.2	159.2	159.2	159.2	158.9	158.1	155.3	146.9	124.8	80.38	26.26
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
Tear	10	10.5	**Mean**	10.5	10.5	10.5	10.5	10.5	10.48	10.43	10.25	9.692	8.232	5.303	1.733
Strength (W)	9.597	1.342	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	998	630	0	0	0
Tear	7	7.5	**Mean**	7.5	7.5	7.5	7.5	7.5	7.485	7.448	7.32	6.923	5.88	3.788	1.238
Strength (F)	6.597	1.342	**# Accepted**	999	1000	1000	1000	1000	1000	1000	1000	904	1	0	0
Seam	70	100	**Mean**	100	100	100	100	100	99.8	99.3	97.6	92.3	78.4	50.5	16.5
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
Spray	90	98.17	**Mean**	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2
Rating (UL)	84.966	8.68	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	979	4	0	0
Spray	90	98.17	**Mean**	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2
Rating (L)	86.64	8.68	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	973	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	999	953	533
Water (L)	20 (max)	13.7	**Mean**	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14
Adsorption	23.69	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	937	253
Chem (UL)	1.3	2.32	**Mean**	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	678	0
Chem (L)	1.3	2.32	**Mean**	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383
Adsorption	1.118	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	384	0

Table 10. Example of Slow Degradation

AF Sample Plan II, Weibull (.07,7)															
	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Break	246	246	**Mean**	245.8	245.5	244.3	241.8	236.4	226.6	209.6	183	146.6	103.3	60.27	27.06
Strength (W)	190	27.22	**# Accepted**	941	932	895	790	372	10	0	0	0	0	0	0
Break	159.17	159.17	**Mean**	159	158.9	158.1	156.5	153	146.6	135.6	118.4	94.87	66.85	39	17.51
Strength (F)	115	9.73	**# Accepted**	928	916	848	540	41	0	0	0	0	0	0	0
Tear	10.5	10.5	**Mean**	10.49	10.48	10.43	10.32	10.09	9.671	8.946	7.812	6.258	4.41	2.573	1.155
Strength (W)	10	1.342	**# Accepted**	938	939	914	810	464	34	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	7.493	7.485	7.448	7.373	7.208	6.908	6.39	5.58	4.47	3.15	1.838	0.825
Strength (F)	7	1.342	**# Accepted**	941	944	914	861	667	219	5	0	0	0	0	0
Seam	100	100	**Mean**	99.9	99.8	99.3	98.3	96.1	92.1	85.2	74.4	59.6	42	24.5	11
Strength	70	10	**# Accepted**	940	935	895	764	322	4	0	0	0	0	0	0
Spray	98.17	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (UL)	90	8.68	**# Accepted**	951	947	937	877	669	156	0	0	0	0	0	0
Spray	98.17	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (L)	90	8.68	**# Accepted**	951	948	903	797	425	17	0	0	0	0	0	0
Water (UL)	13.7	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	20 (max)	9.55	**# Accepted**	963	962	958	956	950	929	881	743	501	217	49	8
Water (L)	13.7	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	20 (max)	9.55	**# Accepted**	953	962	961	930	936	892	764	527	201	21	2	0
Chem (UL)	2.32	2.32	**Mean**	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.3	0.29	**# Accepted**	966	957	955	921	771	415	38	0	0	0	0	0
Chem (L)	2.32	2.32	**Mean**	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.3	0.29	**# Accepted**	954	953	926	856	613	136	0	0	0	0	0	0

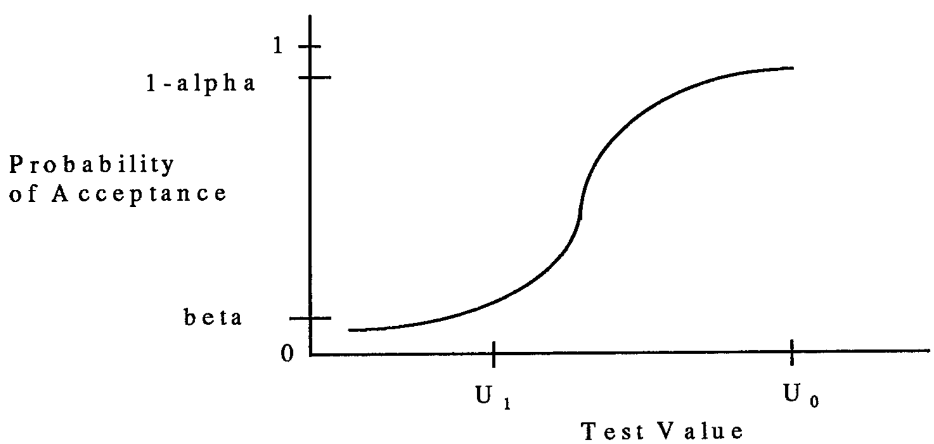


Figure 11. Example of an O.C. Curve

4.3 *Pre-Posturing Results*

Recall that the Pre-Posturing sampling plan samples the same amount of suits as the original sampling plan. The difference is that the Pre-Posturing sampling plan does not sample the same amount of suits every year, but samples fewer suits in the earlier years and more suits in the later years. We can compare the results of this methodology to the results of the original sampling plan.

When we evaluate the results of a sampling plan, we will treat each test in each year as an independent event. The reason for this is that we do not want to make the decision to accept or reject a population of suits, but we want to be able to accurately find when the suits' characteristics have degraded below the minimum requirement. We will still use the terms accept and reject to indicate whether a methodology determines the characteristic is above or below the minimum requirement.

The Pre-Posturing and original sampling plan have eight different years where the number of suits sampled differ between the two methodologies. These are years 5, 6, 7, 8, 11, 12, 13 and 14. With six degradation functions, and eleven different suit tests, these combinations of years, degradation functions, and tests give us a total of 528 simulation results that can be compared between the two methodologies. Simulations for the Pre-Posturing sampling plan were run only once, using Condition I values.

When comparing the two methodologies, we will count as significant only those results that have a difference of 5% or more between the two methodologies. Out of the 528 simulations, only 43 (8.14%) of the simulations have a significant difference of 5% or more. Table 11 shows the years in which the significant differences between the simulations occur and the number of suits accepted in those years. Note that the data in Table 11 is taken from all of the simulations run for the Pre-Posturing and original sampling plan using Condition I values. It is interesting to note that all of the significant differences occur in the simulation runs where the suits should be rejected and

none of the significant differences are in runs where the suits should be accepted. We define that a suit should be rejected when a characteristic's true mean degrades below the minimum requirement U_0, and a suit should be accepted when a characteristic's true mean is above the minimum requirement U_0.

The reason for the differences between the two methodologies being only in simulations where the suits should be rejected is that in both methodologies, the critical region is fixed strictly by the U_0 value in terms of α and the standard deviation. There is no regard for U_1 or β. Therefore both methodologies always insure that there is only a 5% chance of rejecting a good suit without regard to the probability of accepting a bad suit. When the characteristics' true means are at U_0, the Pre-Posturing and original sampling plan will both accept the suits 95% of the time, as the results of the simulations show (See Appendix B, AF and Pre-Posturing Spreadsheets).

Observing Table 11, notice that the years in which each respective sampling plan does better, i.e., accepts less suits, can clearly be divided by the years 5 through 8 and the years 11 through 14. The reason is quite simple. The Pre-Posturing plan has more suits available for sampling in the later years than does the original sampling plan, whereas the original sampling plan has more suits available for sampling in the earlier years than does the Pre-Posturing plan. When the characteristics degrade below their minimum requirement, more suits are needed to accurately sentence the suits as reject or accept. Therefore, as a characteristic degrades below its minimum requirement, whichever sampling plan has the greater number of suits to sample when this occurs will reject a larger percentage of suits.

The whole concept behind the pre-posture plan is to "posture" more of the suits in the years where it is believed the characteristics will degrade close to the minimum requirement. As the true mean nears the minimum requirement, more suits need to be sampled to get a decent β value. In the simulations, many of the suits degrade earlier than the pre-posturing plan expects and

the pre-posture plan has fewer suits in the earlier years, thus resulting in greater errors. The success of the Pre-Posturing plan relies on fairly accurate prior knowledge as to when most of the characteristics start to degrade below the minimum requirement. This plan will succeed only if you know in which years to posture the majority of the suits for sampling. In fact, not only will the plan not succeed if you do not posture the suits correctly, but it can do much worse in its ability to reject bad suits, as seen in the bottom half of Table 11.

Table 11. Comparison Between Pre-Posture and Original Sampling Plans

Percentages Of Suits Accepted When They Should Have Been Rejected													
Simulations Where Pre-Posture Plan Fairs Better													
YEAR	11	11	11	12	12	13	13	13	13	13	13	14	14
Original	18.6	32.3	59.6	20.5	56.5	39.3	86.9	63.0	79.8	8.0	72.9	65.0	81.3
Pre-Posture	11.5	19.5	52.2	13.4	51.7	21.9	81.2	53.4	71.9	1.5	63.6	47.3	70.0
YEAR	14	14	14	14									
Original	71.3	38.6	90.8	83.6									
Pre-Posture	59.0	19.4	85.8	71.8									
Simulations Where Original Sampling Plan Fairs Better													
YEAR	5	5	5	5	5	5	5	5	5	6	6	6	6
Original	70.0	54.9	0.2	7.2	47.2	0.9	68.4	0.1	0	19.2	0.6	9.8	73.2
Pre-Posture	93.1	77.9	13.0	46.0	76.0	22.9	86.1	12.4	22.2	56.9	22.3	49.6	86.7
YEAR	6	6	6	7	7	7	7	8	8	8	8	8	8
Original	26.4	0	37.9	13.9	8.6	23.4	75.2	2.4	24.1	1.7	2.3	34.9	77.4
Pre-Posture	64.4	8.3	84.5	30.3	22.0	39.6	80.4	10.6	40.8	9.4	8.6	50.4	83.4

As mentioned, the whole purpose of the pre-posture plan is to use fewer suits in the earlier years where you believe the actual means of the suits are far away from the minimum requirement and to save those suits for later years. A plan that can statistically determine when less suits are needed for sampling is the sequential sampling plan. We will now look at the results of the Aggregated Sequential plan.

4.4 Aggregated Sequential Results

The purpose of constructing the aggregated sequential plan was to deal with the problem of the different tests requiring different numbers of samples in sequential sampling to meet the given α and β requirements. In this methodology, recall that weights are assigned to each of the various tests. The weights sum to one and the heavier weights are given to those tests that are considered to be more important in deciding whether suits should be rejected or accepted. Unlike the other methodologies in this thesis, the Aggregated Sequential sampling method models the decision of the decision maker. This sampling plan takes into account which tests the decision maker believes are of most important, and models this by appropriately assigning weights to each of the tests. For the simulation, we assigned the two Chemical Adsorption tests weights of .25 each. The remaining nine tests were each assigned weights of .0556. These weights sum approximately to one.

The results of the simulations for the Aggregated Sequential plan are displayed in Table 12. The years in which the aggregated sum first degrades below U_0 are surrounded in bold. Note that the average sample size falls below 6 samples in every year. The original sampling plan samples 30 suits per year. In the standard sequential plan, which is introduced in later in Section 4.8, average sample sizes range usually between 5 and 80 samples for each test in any given year.

There are two reasons for such a reduction in sample size using the Aggregated Sequential plan. The first reason is that by aggregating all the results, the variance is reduced. Recall in Section 3.6 after the test results were standardized, all the results were normally distributed with a standard deviation of 1. After the tests are aggregated, the result is a normally distributed random value with a standard deviation of .391. In general, sequential sampling requires less samples to be taken as the standard deviation decreases. The second reason for the smaller sample size is that the chemical adsorption tests are weighted the most heavily. The chemical adsorption tests usually require a small sample size and account for 50% of the weighted values of the Aggregated sample

plan. Conversely, the other less critical tests that require large samples are weighted small enough to have little effect in increasing the sample size.

Table 12. Aggregated Sampling Results

Aggregated Sequential Sample Plan I, Weibull (.065,15)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			Degradation	1	1	1	1	1	0.998	0.993	0.976	0.923	0.784	0.505	0.165
Agg Seq			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
			Avg Sample	2.96	2.95	2.96	2.95	2.96	2.96	2.98	3.05	3.74	4.95	2	1

Aggregated Sample Plan I, Weibull (.07, 7)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			Degradation	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Agg Seq			# Accepted	1000	1000	1000	1000	1000	1000	1000	998	4	0	0	
			Avg Sample	2.96	2.96	2.99	3.01	3.16	3.77	4.04	5	2.07	2	1.04	

Aggregated Sample Plan II, Weibull (.03,1.1)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			Degradation	0.883	0.859	0.836	0.812	0.789	0.766	0.744	0.723	0.701	0.68	0.66	0.64
Agg Seq			# Accepted	1000	1000	1000	1000	1000	1000	999	995	936	731	397	113
			Avg Sample	3.99	4.02	4.19	4.63	4.91	4.99	5	5.05	5.17	4.87	3.9	2.82

Aggregated Sample Plan I, Weibull (.035, .8)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
			Degradation	0.78	0.751	0.723	0.697	0.672	0.649	0.628	0.607	0.587	0.568	0.55	0.533
Agg Seq			# Accepted	1000	998	992	905	567	237	54	10	0	0	0	0
			Avg Sample	4.97	5	5.04	5.11	4.45	3.33	2.51	2.14	2.03	2.01	2	2

Aggregated Sample Plan I, Weibull (.03,.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
			Degradation	0.679	0.654	0.632	0.613	0.595	0.578	0.563	0.549	0.536	0.523	0.511	0.5
Agg Seq			# Accepted	693	307	69	7	3	0	0	0	0	0	0	0
			Avg Sample	4.78	3.6	2.57	2.15	2.05	2.01	2	2	2	2	2	2

Aggregated Sample Plan I, Weibull (.05,2.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
			Degradation	0.969	0.952	0.93	0.904	0.873	0.838	0.799	0.757	0.711	0.664	0.614	0.564
Agg Seq			# Accepted	1000	1000	1000	1000	1000	1000	1000	999	979	463	24	0
			Avg Sample	3.09	3.27	3.63	3.91	4	4.16	4.85	5	5.13	4.11	2.26	2

The results show that since the Chemical Adsorption test is weighted the most heavily, the chemical test naturally has the largest influence on when to fail the population as a whole. If the Chemical Adsorption test shows an accept value, it usually takes a combination of six to seven other tests showing a reject value in order to reject the suit. These results meet the objective of the test: to keep testing if the tests that are deemed important still require testing, and to take away the ability of smaller valued tests to keep requiring suits to be tested just to satisfy the sampling needs of a lesser valued test. While half the weight in the Aggregated Sequential plan is allocated to the Chemical Adsorption tests, the Aggregated accept / reject decision does not exclusively follow the accept / reject decision of the Chemical Adsorption test. Table 13 compares the results to accept or reject the suits based upon the Aggregated Sequential plan and based upon the Chemical Adsorption alone which uses the standard sequential plan, to be discussed in Section 4.8. Note that especially under degradation functions three, four, and five, the Aggregated Sequential plan rejects the suits as a whole indifferent to the fact that the Chemical Adsorption test signifies the chemical adsorption characteristic is still acceptable. This is an example of the less critical tests combining to influence the critical tests.

With this plan we are assuming that the different tests are independent of each other in determining the variance of the aggregated normal distribution. It is pretty unlikely that the warp breaking strength is independent of the fill breaking strength and the same for the two tearing strength tests. At this time we do not have the information available to determine the covariances between the tests. If we are assuming the tests are independent but the true tests actually have a positive covariance, then we have **underestimated** the actual variance of the aggregated sum. If the variance of the aggregated sum is underestimated, then the Aggregated Sequential sampling will require too few samples to be drawn. This is because the larger the variance, the larger the number

of samples that are needed to meet the α and β requirements. The result is that if we assume independence when the tests are not independent, too few samples will be taken and the Type I and II errors will be larger than we want.

Table 13. Aggregate Samples Relative to Chemical Adsorption Samples

		NUMBER OF SAMPLES ACCEPTED (Out of 1000)											
	Test	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
Degradation	Aggregate	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
One	Chem Adsorp.	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1	0
Degradation	Aggregate	1000	1000	1000	1000	1000	1000	1000	998	4	0	0	0
Two	Chem Adsorp.	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0
Degradation	Aggregate	1000	1000	1000	1000	1000	1000	999	995	936	731	397	113
Three	Chem Adsorp.	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Degradation	Aggregate	1000	998	992	905	567	237	54	10	0	0	0	0
Four	Chem Adsorp.	1000	1000	1000	1000	1000	1000	1000	1000	1000	987	717	98
Degradation	Aggregate	693	307	69	7	3	0	0	0	0	0	0	0
Five	Chem Adsorp.	1000	1000	1000	1000	1000	998	974	675	145	25	3	0
Degradation	Aggregate	1000	1000	1000	1000	1000	1000	1000	999	979	463	24	0
Six	Chem Adsorp.	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	972

The Aggregate Sequential plan is a promising plan. As shown by the simulation, few samples are needed in order to satisfy the α and β requirements. The cost of these fewer samples is determining and assigning the weights to be assigned to the tests. This is a decision left to the decision maker. Also, the assumption that the tests are independent may result in too few samples being drawn if covariance actually exists. As the real-life results of sampling become available, it may be possible to determine the covariance between the test results. Since this sampling plan assumes which tests are important from a decision makers point of view, the tests cannot be viewed independently of each other. It is for this reason that we will not compare how accurately the plan accepts or rejects suits compared to the other sampling plans in which the tests are treated independently.

4.5 Measure of Effectiveness

Before we evaluate the results of the four remaining methodologies we will present a measure of effectiveness to measure the results. The first two methodologies presented, the Pre-Posturing and Aggregated Sequential plans, will not be evaluated with the measure of effectiveness. The reason for this is that the sequential methodologies accomplish what the pre-posturing plan tries to do: take the most samples where they are needed. We have shown that the success of the Pre-Posturing methodology is very dependent on accurately forecasting which years the suits will start to degrade below the minimum requirements. If we knew which years the suits would start to degrade, we would not need sampling at all. The Aggregated Sequential plan is not evaluated with a measure of effectiveness since this plan is different in and of itself. This is the only plan where the tests combine to reject or accept a suit and the only plan that takes into account the decision maker's thoughts in assigning the relative importance to the various tests.

We need a measure of effectiveness that reflects the performance of the various methodologies, yet is simple enough for a non-statistician to understand. Our first thought was to assign a cost function to the results. This proves to be get too unwieldy for the scope of this thesis, since we would not only need the costs for taking samples, but also the costs and probabilities of making a Type I and Type II error. Costs that would need to be determined include the cost of an Air Force member's death and the cost of the remaining life of a suit if it were rejected too early. We would also need the probabilities of chemical attacks in a given length of time and the probability that an airman involved in a chemical attack was wearing a degraded suit. This measure of effectiveness would prove to rely too much on the accuracy of the cost function as opposed to the actual performance of the methodologies.

The measure of effectiveness we chose to use is one that measures the accuracy of the methodology in correctly rejecting a suit when a characteristic has degraded below the minimum

requirement. This is accomplished by finding the percentage of suits that were correctly rejected in the same year the suit degraded past the minimum requirement. The measure of effectiveness also finds the percentage of suits that were rejected earlier than they were supposed to and which methodologies rejected suits after the suits already passed below the minimum requirement.

We get our measure of effectiveness by finding the years in which the characteristics degrade below their minimum requirements. We then find the percentage of suits rejected in the same years as when the characteristics degraded. We regard this percentage as the percentage of suits rejected correctly. Similarly, we find the percentage of suits that were rejected one year early, one year late, two years early, two years late, etc. For each methodology we find the average percentages for the different characteristic tests. We give a measure of effectiveness percentage that is the average of how the tests faired in accurately rejecting a characteristic that has degraded below the minimum requirement. See Tables 14 and 15 for the measure of effectiveness results.

For the measure of effectiveness, the greater percentage of suits that were rejected in the Year Failed column, the more success the methodology has in correctly rejecting suits the same year a characteristic falls below its minimum requirement. In Tables 14 and 15, the successful methodologies are the ones in which the majority of the suits are rejected in the year the characteristic fails. For example, in Table 15, the Truncated Sequential result in Degradation Function 5 is highly successful, rejecting 73.07% of the suits in the correct year. Conversely, the methodologies which are not as successful are those in which many suits are rejected several years early or several years late. An example of this is the Truncated Sequential plan in Table 14 in Degradation Function 6, where over 41% of the suits were rejected over four years late. The Average Number of Samples column gives the average number of samples used over the lifetime of the suit for that particular sampling plan.

4.6 *Attribute Bayesian Results*

The Bayesian methodology does not fare as well as we had hoped. In Table 14 under the Year Failed column, the Bayesian results show that the Bayesian sampling plan is not effective in rejecting suits after they have failed. Compared to the other sampling plans, the Bayesian is the least effective in all six degradation functions. The results under the Years Late columns show that the Bayesian methodology always lags behind the other methodologies in being able to properly reject a degraded suit. The Bayesian methodology clearly does not do as well as the other methodologies.

Table 14. Measure of Effectiveness Results, Condition II Simulation

PERCENTAGE OF SUITS METHODOLOGIES REJECTED, CONDITION II SIMS												
METHOD	> 4 Years Early	4 Years Early	3 Years Early	2 Years Early	1 Year Early	Year Failed	1 Year Late	2 Years Late	3 Years Late	4 Years Late	> 4 Years Late	Avg # of Samples
	DEGRADATION FUNCTION 1											
ORIGINAL	13.4	4.05	3.68	3.91	5.91	16.6	34.5	9.32	6.64	2.01	0	360
SEQUENTIAL	6.86	2.08	2.01	1.85	3.24	9.35	23.5	37.6	13.2	0.29	0	331.78
TRUNC. SEQ.	9.44	2.32	2.2	2.35	2.64	5.47	17.5	45.7	10.7	1.36	0	266.24
BAYESIAN	2.86	1	1.29	1.14	1.57	2.43	18.7	26.1	43.6	1.29	0	321.47
	DEGRADATION FUNCTION 2											
ORIGINAL	0	0	5.22	5.2	7.21	13.7	26.6	24.3	6.89	3.88	6.96	360
SEQUENTIAL	0	0	2.59	2.67	3.6	7.03	17	15.9	21.1	22.8	7.26	263.9
TRUNC. SEQ.	0	0	4.09	3.21	4.03	5.72	11.8	12.4	29	23.1	6.66	202.207
BAYESIAN	0	0	1.71	0	2	1.43	6.43	16.7	17.3	22	30.4	233.14
	DEGRADATION FUNCTION 3											
ORIGINAL	0	0	0	0	0	82.9	3.96	2.38	2.42	2.07	5.98	360
SEQUENTIAL	0	0	0	0	0	53.4	16.2	12.5	7.59	4.43	5.88	204.87
TRUNC. SEQ.	0	0	0	0	0	48.5	19.7	12.8	6.43	4.99	7.48	109.5
BAYESIAN	0	0	0	0	0	30.4	0	15.3	4.29	3.86	37.1	151.26
	DEGRADATION FUNCTION 4											
ORIGINAL	0	0	0	0	0	87.3	4.15	3.12	2.21	1.32	1.94	360
SEQUENTIAL	0	0	0	0	0	83.3	10.3	4.26	1.51	0.43	0.15	207.2
TRUNC. SEQ.	0	0	0	0	0	85.6	8.56	3.55	1.38	0.52	0	65.03
BAYESIAN	0	0	0	0	0	53.1	10.3	9.86	8.14	4	14.6	125
	DEGRADATION FUNCTION 5											
ORIGINAL	0	0	0	0	0	90.9	4.59	2.18	1.18	0.55	0.57	360
SEQUENTIAL	0	0	0	0	0	94.6	4.47	0.76	0	0	0	181.2
TRUNC. SEQ.	0	0	0	0	0	93.9	3.67	1.42	0.59	0	0	51.86
BAYESIAN	0	0	0	0	0	83.6	5.43	2.43	1.14	1.57	5.86	176.61
	DEGRADATION FUNCTION 6											
ORIGINAL	0	0	0	0	0	34.7	28	16.6	6.58	2.77	11	360
SEQUENTIAL	0	0	0	0	0	18.7	17.5	10	9.07	12.7	32	230.16
TRUNC. SEQ.	0	0	0	0	0	15.8	16	4.03	8.97	13.9	41.3	175.26
BAYESIAN	0	0	0	0	0	3	5.57	15	12.6	6.43	54.7	185.22

Table 15. Measure of Effectiveness Results, Condition I Simulation

PERCENTAGE OF SUITS METHODOLOGIES REJECTED, CONDITION I SIMS												
METHOD	> 4 Years Early	4 Years Early	3 Years Early	2 Years Early	1 Year Early	Year Failed	1 Year Late	2 Years Late	3 Years Late	4 Years Late	> 4 Years Late	Avg # of Samples
	DEGRADATION FUNCTION 1											
ORIGINAL	0	0	0	0	0.56	58.6	34	0	0	0	0	360
SEQUENTIAL	0	0	0	0	0	76.7	23.8	0	0	0	0	1017.2
TRUNC. SEQ.	0	0	0	0	0.57	76.3	17.4	0	0	0	0	282.48
	DEGRADATION FUNCTION 2											
ORIGINAL	0	0	0	0	0.98	60.9	27.5	7.54	0	0	0	360
SEQUENTIAL	0	0	0	0	0	82.1	17.5	0	0	0	0	783.4
TRUNC. SEQ.	0	0	0	0	2.48	72.4	19.8	2	0	0	0	256.1
	DEGRADATION FUNCTION 3											
ORIGINAL	0	0	0	0	1.07	44.9	36.3	9.43	1.42	0	0	360
SEQUENTIAL	0	0	0	0	0.81	65	22.3	3.09	0	0	0	803.5
TRUNC. SEQ.	0	0	0	0.63	3.06	60.3	22.5	4.68	0	0	0	343.84
	DEGRADATION FUNCTION 4											
ORIGINAL	0.71	0	0	0.57	1.56	47.7	13.7	5.41	0.59	0	0	360
SEQUENTIAL	0	0	0	0	1.23	58.1	26.2	2.28	0	0	0	1920.8
TRUNC. SEQ.	2.42	0.91	0.82	1.62	3.68	57.4	22.6	4.31	0.18	0	0	355.72
	DEGRADATION FUNCTION 5											
ORIGINAL	0.87	0	0	0.67	1.23	59.5	8.41	5.31	4.38	2.67	0	360
SEQUENTIAL	0	0	0	0	0.58	71.2	17.2	4.17	3.11	0	0	3553.9
TRUNC. SEQ.	2.64	0.97	1.07	1.68	2.94	73.1	11.3	3.49	1.16	0	0	349.62
	DEGRADATION FUNCTION 6											
ORIGINAL	0	0	0	0	1.6	22	29.5	9.92	2.77	3.84	2.64	360
SEQUENTIAL	0	0	0	0	1.18	34.1	34.7	2.27	7.24	4.29	0	901.4
TRUNC. SEQ.	0	0	0	1.38	5.81	34.2	33.2	4.86	4.06	4.04	0.82	348.13

While the Bayesian method does use prior knowledge of the probability that a suit will pass a test and uses the information gained from earlier tests, too much information is lost in converting the variable results of the tests into attribute (pass / fail) results. It throws away the information that variable results give in the distance away a test result is from its minimum requirement. The Bayesian prior information is not enough to make up for the lost variable information. Since the results are clearly inferior to the other three methodologies, the Bayesian methodology is not simulated under the Condition I simulations.

To be fair to the Bayesian methodology, it should be reminded that we originally thought the data would be attribute pass / fail data. When we discovered that our data would be variable test data, we decided to try the attribute Bayesian methodology anyway. Appendix C gives the results of a comparison we did in which we compared the Bayesian attribute plan to the original sampling plan in which the original sampling plan also used attribute data. The results show that the Bayesian plan still does not fare well when compared to other methodologies that also use attribute data.

After reviewing the results in which the Bayesian algorithm did not perform as well as the original sampling plan using attribute data, we studied the Bayesian methodology deeper in depth. We feel that the algorithm in which the Bayesian is used is not appropriate in detecting the suits' degradations. The reason for this is that the hypothesis test is set up so that the current reliability of the suit is always accepted with a probability of $1-\alpha$. Each year that the suits degrade, the believed reliability of the suits is updated. The suits, with their updated reliability, still have a $1-\alpha$ probability of being accepted, even though their reliability has degraded. So as the suits degrade, the probability of an **individual suit** passing a test decreases. However, the probability that the **population** will be accepted at the new updated reliability stays fixed at $1-\alpha$. Perhaps a new Bayesian methodology that utilizes variable data in determining when a system has degraded below a minimum requirement would be useful.

4.7 Standard Sequential Results

The standard sequential methodology allows each test to run as many tests as needed to satisfy the α and β requirements. The average number of samples used in the lifetime of each test is given along with the percentage of suits rejected in Tables 14 and 15. Note that in the Condition I simulations, where the U_0 and U_1 values are closer together, more samples are needed to meet the

α and β requirements. In Degradation Function 5 of the Condition I simulation, this sampling method averaged 3554 samples throughout the lifetime of the suits. Clearly, 3554 samples would destroy more suits than the Air Force is willing to part with. While the sequential methodology is infeasible to run because of the high number of samples required by some of the tests, it gives good information on the number of samples needed to satisfy the most demanding α and β requirements on the various tests. The results of the measure of effectiveness also give a good benchmark from which to gauge the success of the other methodologies.

When the standard sequential's results in Tables 14 and 15 are compared to the Truncated Sequential's (Section 4.9) results, it is noticed that the large differences in sample sizes result in relatively little improvement in being able to reject a suit in the correct year. For example, the average sample sizes over all degradation functions and Condition values for the standard sequential and Truncated Sequential are 867 and 234, a difference of 633 suits. The average percentage of suits rejected correctly is 54.5 and 52.4 respectively. The difference of 633 suits gives only a 2.1 percentage point increase in accuracy. This is certainly not an effective way of sampling suits.

As mentioned earlier, the problem with unbounded sequential sampling is that some test may always be lingering in the "continue sampling" zone of the sequential test, pushing up the number of samples, while all other tests may have made their accept or reject decision after a few samples. This is the inherent problem with sequential sampling. After evaluating the results for the original sampling plan in the next section, we will evaluate the Truncated Sequential sampling, which puts an upper limit on the number of suits to sample using sequential sampling.

4.8 Original Sampling Plan Results

The original sampling plan, as mentioned earlier, is designed to meet the α specifications of the tests only. It is not responsive to the β requirements at all. Therefore, this methodology always insures that it accepts the suits with a .95 probability when the actual characteristics' means are at the U_0 level. This gives this test the ability to be very successful in not rejecting the suits too early. This is a characteristic that the contractor would like very much. Unfortunately, the downside is that since no attention is given to the β value, this methodology could be late in rejecting a suit. This methodology may give the indication that the suit is good when it actually should be rejected, and this could occur more often than the Air Force should be comfortable with.

Table 16 shows the theoretical β values for the original sampling plan for both Condition I and Condition II values of the tests. For instance, with the Warp Break Strength, β is .398 and 0 for Condition I and II values respectively. This is saying that when Warp Break Strength is at its actual U_1 value, the suits will be rejected 39.8% of the time for Condition I values and 0% of the time for Condition II values. The Air Force would like the suits to be rejected 10% of the time when the actual mean of the Warp Break Strength is U_1. Note that the Beta values in Condition II are smaller than those from Condition I. The reason for this as mentioned at the beginning of this chapter is that the distance between the U_0 and U_1 values is much greater in the Condition II values. When viewing Table 16 recall that L and UL stand for Laundered and Unlaundered and that W and F stand for Warp and Fill.

The fact that the beta values have such small values in some of the tests with the Condition II values has a significant effect on the measure of effectiveness values for Condition II simulations. Table 14 shows that in most cases, the original sampling plan rejects significantly more suits than

do the other methodologies in the Year Failed column. As a whole, the original sampling plan rejects suits in a more timely matter than do the other methodologies in Condition II simulations.

Table 16. Theoretical Beta Values

	True Value for Beta	
TEST	**Conditon I**	**Condition II**
Break Strength (W)	0.398	0
Break Strength (F)	0.060	0
Tear Strength (W)	.348	.343
Tear Strength (F)	.585	.348
Seam Strength	.274	0
Spray Rating (UL)	.282	.011
Spray Rating (L)	.574	.140
Dynamic Adsorption (UL)	.888	.118
Dynamic Adsorption (L)	.916	.403
Chemical Adsorption (UL)	.761	0
Chemical Adsorption (L)	.824	0

For Condition I simulations, a different picture appears for the original sampling plan. In Condition I simulations, the original sampling plan rejects suits in a less timely matter than do the other two plans. Whereas very few suits are rejected early, more suits are rejected late, comparative to the other two methodologies.

The reason for the differences has to do with the Beta values. With the Condition I values, the actual Beta values are relatively high, so with the fixed sampling, we expect to see more suits being rejected later than they should be. On the other hand, with the Condition II values, the actual

Beta values are fairly low and very close to zero for some of the tests. When the actual Beta values are below the required .10 value, over-sampling occurs. The decision maker was willing to take a Beta risk of .10, but is now paying for a smaller Beta risk than he needs. This is a problem with fixed sample methodologies. The methodologies are usually devised to satisfy either α or β, but not both. In this sampling plan, the methodology will satisfy the α requirement, but whether it satisfies the β requirement depends on how far the value U_1 is from U_0. We feel that it is important to be able to control the Type II error.

4.9 Truncated Sequential Results

The truncated sequential sampling results appear to be the most promising. By truncating the tests earlier, there is some reduction in accuracy when compared to the standard sequential plan. In section 4.7, it was shown that when using the Truncated Sequential plan instead of the standard sequential, the average reduction of 633 samples decreased the percentage of suits rejected in the correct year by only 2.1 percentage points. The case in which the largest difference of values in the Year Failed column occurred was 10 percentage points, which was in Degradation Function 2 in Condition I sampling. All other differences between the Year Failed columns are less than five percentage points, and many of them have less than one percentage point in difference. These are certainly small percentages to pay when being able to control and reduce the sequential sample size.

When comparing the truncated sequential to the original sampling plan, the original sampling plan performs better in the Condition II simulations and the Truncated Sequential performs better in the Condition I simulations. The reason for this difference is largely due to the difference of the distances between U_0 and U_1 for Condition I and II values. When actual real world sampling takes place, a reasonable choice for U_o and U_1 will fall between the two sets of values of U_0 and U_1

used in the simulations. The two sets of values chosen for the simulations are at the wide ends of the lower and upper scale for distance between the U_0 and U_1 values. This being the case, we set up another set of values, which we will call Condition III values, that more closely model the U_0 and U_1 values that will occur in actual sampling.

The value chosen for U_1 will be equal to the minimum requirement declared for each test by the Air Force. This is the same value for U_1 as it was in Type II sampling. Our choice for U_0 is half the distance between U_1 and the starting mean for the test. The distance between U_o and U_1 is now exactly half the distance as it was in Type II simulations. These values can be put into words as saying "when the characteristics degrade from their starting means to halfway to the minimum requirement, we want to accept them 95% of the time, when the characteristics have degraded to their minimum requirement, we want to accept them only 10% of the time". The simulations were run only for the Truncated Sequential and the Original sampling plans. The results for the measurement of effectiveness for Condition III simulations are in Table 17.

Table 17 shows the results are fairly equal for the percentages of suits rejected correctly. To get a clearer idea of how the two methods compare, we averaged: 1) the percentage of suits rejected correctly; and 2) the percentage of suits that were rejected correctly, plus or minus one year. The average percentages of suits rejected in the correct year were 50.43% and 50.23% and the average percentage of suits that were rejected within one year of the correct year were 75.46% and 74.14%, for the original and Truncated Sequential sampling plans respectively. The differences are so small that they are negligible. However, the Truncated Sequential plan is able to get this information using considerably fewer number of suits. The Truncated Sequential plan averages 205 suits over the lifetime of the suits while the original sampling plan always uses 360 suits. Using the values for Condition III simulations, the two methodologies appear to be equal in accuracy, but not efficiency.

The two advantages that the Truncated Sequential sampling plan has over the original plan is that it is able to control its Type II errors in addition to its Type I errors and the Truncated Sequential plan reduces the number of samples used. The original sampling plan averaged 360 suits, whereas the Truncated Sequential plan averaged about 205 suits. This is a difference of 155 suits on average.

Table 17. Measure of Effectiveness, Condition III Simulations

PERCENTAGE OF SUITS METHODOLOGIES REJECTED, CONDITION III SIMS												
METHOD	> 4 Years Early	4 Years Early	3 Years Early	2 Years Early	1 Year Early	Year Failed	1 Year Late	2 Years Late	3 Years Late	4 Years Late	> 4 Years Late	Avg # of Samples
	DEGRADATION FUNCTION 1											
ORIGINAL	0.49	0.14	0.11	0.24	1.88	68	27.3	0.06	0	0	0	360
TRUNC. SEQ.	3.19	0.74	0.96	1.3	5.13	66	21.9	0	0	0	0	298.56
	DEGRADATION FUNCTION 2											
ORIGINAL	0.07	0.16	0.09	0.23	1.56	31.4	46.7	13.5	4.94	1.25	0	360
TRUNC. SEQ.	0.09	0.92	0.93	1.49	3.78	34.6	50.3	6.28	1.24	0.31	0	243.21
	DEGRADATION FUNCTION 3											
ORIGINAL	0.2	0.28	0.31	0.51	1.06	38.2	22.3	15.6	6.46	2.91	0	360
SEQUENTIAL												
TRUNC. SEQ.	0.45	0.54	0.62	1.16	1.33	39.3	6.32	13.3	17.8	11	0.6	210.25
	DEGRADATION FUNCTION 4											
ORIGINAL	0	0	0	1.35	1.35	67.7	8.3	6.23	3.33	2.02	8.58	360
TRUNC. SEQ.	0	0	0	1.8	1.8	66.8	12.4	5.76	5.41	4.52	3.27	129.25
	DEGRADATION FUNCTION 5											
ORIGINAL	0	0	0	0	0	81.4	4.35	2.19	2.14	1.96	7	360
TRUNC. SEQ.	0	0	0	0	0	83.6	8.52	4.53	1.71	0.81	0.83	100.47
	DEGRADATION FUNCTION 6											
ORIGINAL	0.12	0.12	0.14	0.27	1.36	15.8	35.4	24.6	10.2	3.34	0	360
TRUNC. SEQ.	0.19	0.22	0.52	0.59	3.88	11.1	28.1	42	11	1.41	0	249.21

4.10 Summary

We have reviewed and analyzed the data and derived results for each methodology. The Pre-posturing method was shown not to be superior to the original sampling plan and the Aggregated sequential plan was shown to have considerably reduced the number of samples drawn due to its small variance. The Aggregated sequential plan also made the assumption that the tests are independent of each other. The Bayesian plan was shown to have been disappointingly unsuccessful and the standard sequential plan needed too many samples to be feasible. This left us with the original sampling plan and the Truncated sequential plan. These last two sampling plans performed equally as well according to the simulation results and measure of effectiveness. In the next chapter, we will give our conclusions and recommendations.

5. *Conclusion*

5.1 Findings of Sampling Methodologies

The purpose of this thesis was to find a sampling methodology that would monitor the shelf-life of the Air Force's Chemical Defense coverall. The goal was to find a methodology that would be able to effectively detect the degradation in quality of the suits, while at the same time minimize the number of samples needed to accurately do this. Based on the results of the study and simulations, a brief description is given on the findings for each of the six methodologies presented in this thesis.

5.1.1 Pre-Posturing Sampling Plan.

The purpose of the Pre-Posturing sampling method was to distribute the suits before sampling began in such a way that fewer suits would be sampled in the earlier years when less samples were thought to be needed and more suits would be sampled in the later years when more suits would be required to be tested. In doing so, it was hoped that the Type II error of accepting a bad suit would be reduced.

The simulations reinforced the belief that the success of this methodology was largely a factor of being able to accurately predict when the suits' characteristics would degrade below the set minimum requirement. If the degradation of the suits occurred at one of the years in which few suits were postured, the methodology was shown to be ineffective at rejecting a bad suit. This methodology relied too much on prior information in knowing when the suits would degrade in their reliability in order to be a useful methodology.

5.1.2 Aggregated Sequential Sampling.

The purpose of this sampling plan was to assign weights to each of the tests according to the decision maker's expert opinion on which tests were more important in determining the reliability

of the suits. This was the only methodology which took into account the decision maker's opinion on how the tests would relate to one another.

The simulations showed when weights were added to the tests and an aggregated sum was achieved, there was a substantial reduction in the number of samples needed for the lifetime of the tests. The average number of samples needed for this test was under 60 samples per year, as compared to the original sampling plan which averaged 360 per year and the Truncated Sequential plan that averaged around 323 suits per year over the same degradation functions. The one uncertainty of the test was the assumption of independence between the tests. If independence is assumed but positive covariance exists between the tests, then the variance of the aggregated sum is underestimated. This will result in too few samples being drawn to meet the given α and β requirements. The actual Type I and II errors would be larger than believed. The magnitude of these errors relies on the size of the covariance between the tests and further study is needed to determine the effects of covariance.

5.1.3 Attribute Bayesian Sampling Plan.

This plan converted the variable test results to attribute pass/fail results and used Bayesian prior knowledge to detect the degradation of the suits. The simulations showed that converting the variable results to attribute data resulted in too much loss of information and this particular methodology utilizing Bayesian statistics was not suitable for detecting the degradation of the chemical suits. The Bayesian concept does have hope however, if a similar plan that utilizes variable data can be incorporated with the Bayesian concept in detecting the degradation of the chemical suits' quality.

5.1.4 Standard Sequential Sampling Plan.

This sampling plan used unbounded sequential sampling to determine the degradation in quality of the chemical suits. Due to some of the tests requiring large samples to make an accept

or reject decision, this test proved to be highly inefficient. The average sample size for the lifetime of the suit was 867 samples using this methodology. This was by far the largest average out of all the other sampling methodologies. It was also shown that the increase in effectiveness by using such a large sample was minimal. The Truncated Sequential used on average 633 fewer suits, yet its ability to reject suits in the correct year only decreased by 2.1 percentage points. The standard sequential test is much too inefficient to be of useful value for sampling the chemical defense coveralls.

5.1.5 Original Sampling Plan.

The original sampling plan sampled a fixed amount of suits every year and ensured that the probability of a Type I error would be .05. It was unable to have any effect in controlling the Type II error however. While this sampling methodology compared well to the other methodologies in the Condition II simulations, it was largely an effect due to the distances between U_0 and U_1 for the various tests. When the distance between U_o and U_1 is large, the original sampling plan does well, but when these differences are small, the sampling plan does not fare so well. The plan is too inflexible to the distance between U_o and U_1, which is a variable that cannot be controlled by this sampling plan. The result is the possibility of a large Type II error, which results in degraded suits being labeled as acceptable.

5.1.6 Truncated Sequential Sampling Plan.

The Truncated Sequential plan uses the concepts of the standard sequential plan, but puts a limit on the upper bound of suits that can be sampled. This plan starts out with 360 suits available for sampling, just as the original sampling plan does. If few suits are sampled in the earlier years of testing, it is able to save these suits for testing in the later years if necessary.

This sampling plan proved to be the most flexible and efficient sampling plan. This plan performed as well or better than the other methodologies in the Condition I and III simulations. In

the Condition II simulations, this sampling plan did not do as well as the original sampling plan did. Since the distance was so great between U_o and U_1 in the Condition II simulations, the original sampling plan had very small Beta values (Table 16). The original sampling plan performed better in the Condition II simulations, but it over-sampled, giving the test manager smaller Beta values than were requested. The Truncated Sequential sampling plan however, is flexible to the various distances that may occur between U_0 and U_1, and is able to control the Type II error.

5.2 Recommendations

I feel that the Truncated Sequential sampling plan was shown to be the best sampling plan to monitor the shelf-life of the chemical defense coveralls. This plan is flexible to both the α and β requirements and flexible to the distances between U_o and U_1 that are set by the decision makers. This plan was also able to reduce the number of samples used to test the suits when compared to the original sampling plan.

The sampling plan is relatively easy to implement. It is required that a standard deviation is known or estimated for the various tests that will be used in sampling. These standard deviations are available through the research and development and pre-testing of the chemical defense suits. Additional data to help determine the standard deviations will also be available once the baseline tests are run on the coveralls.

Sequential Sampling will require the ones who perform the actual tests to continually update the sequential test values after each test is performed on a suit. This way, when all the tests make an accept or reject decision, the sampling can be stopped immediately to prevent any unnecessary sampling.

I also believe that the Aggregated Sequential sampling plan has potential. The number of samples used was greatly reduced by aggregating the test results. This plan requires that the

decision makers determine how much influence they would like each test to have in determining the accept / reject decision of the suits. Weights are assigned to each test in relative importance and the weights should sum to one.

This plan needs analysis in determining the effects of covariance between the tests on the sequential sampling. Covariance can possibly be estimated from the research and development and pre-testing. Another alternative is to evaluate what the effects would be if the tests were assumed to be independent but covariance actually existed. Perhaps the Aggregated Sequential plan could then be modified to account for the unknown covariance.

If neither of these plans is implemented, I feel it is extremely important that some consideration of the probability of a Type II error is taken into consideration. Recall that when a Type II error does occur, it is labeling degraded suits as reliable. The danger then exists that commanders in the field believe they have adequate protection against chemical warfare when in fact, the protection may be severely limited due to having degraded suits. Rather than setting the original sampling plan such that $\alpha = .05$, maybe the sampling plan could be designed such that $\beta = .05$. Whereas a small α error will prevent suits from being rejected while they are still good, a small β error will prevent suits from being accepted when they are no longer good.

5.3 Recommendations for Further Research

There is still more work and studies needed to fully understand this topic and we now give our recommendations for further research.

1. A development of Launer and Singpurwalla's Bayesian plan to use variable data as opposed to their attribute data. Information is lost when converting variable data to attribute data. A sampling plan incorporating Bayesian statistical methods with variable data may prove to be quite effective.

2. A study using cost analysis or decision analysis to determine the optimal settings of α and β. As the values for α and β decrease, more sampling is needed, but the Type I and Type II errors decrease. A study to find the optimal values for α and β would be valuable. Along with this study could be a determination of the optimal number of samples that should be allowed in the Truncated Sequential sampling plan before the sampling is truncated.

3. A study to test the sensitivity of assuming a normal distribution when the actual distribution is of some other type. We assumed the samples were pulled from a normal distribution. It would be interesting to see how the results are affected if the distribution deviated slightly or greatly from a normal distribution.

4. A methodology to test the suits and determine if there is a difference in the degradation between the various lots. A sampling plan could be devised that would be able to detect a difference in degradation between lots. If differences were detected, the plan would be able to reject the bad lots while keeping the good lots.

5. A study on the effects of covariance in the Aggregated Sequential sampling plan. This plan showed a substantial reduction in the number of samples to be used when the tests were aggregated. Uncertainty exists however, on how the presence of covariance would effect the results.

6. A study that would take into account the possibility of the sampling tests being less than 100% accurate. This would add complexity to the sampling model. The study could also determine what the effects are when assuming 100% accuracy, when the tests are actually less than 100% accurate.

7. A study that could take into account the effect that various environmental conditions have on the reliability of the suits. In this thesis, the suits that are to be sampled are taken from an

environmentally controlled warehouse. It would be interesting to see how the effects of storing the suits in less than perfect conditions affects the reliability.

Appendix A. Computer Programs

This appendix lists the computer programs that were used to simulate the sampling methodologies. The simulations were run in SLAM II with the exceptions of the Bayesian and Truncated Sequential plans which were run using FORTRAN. The SLAM II programs are presented in their text form only.

A.1 Original Sampling Plan

```
CREATE,.01,,,30000,1;
   ACTIVITY,,II.LT.1;
   ACTIVITY,,,ZAAH;
   ASSIGN,II=1;
   ACTIVITY;
ZAAH ASSIGN,ATRIB(1)=XX(II)*246.0,ATRIB(5)=XX(II)*10.5,ATRIB(3)=XX(II)*159.17,
   ATRIB(7)=XX(II)*7.5,ATRIB(9)=XX(II)*100.0;
   ACTIVITY;
   ASSIGN,ATRIB(2)=RNORM(ATRIB(1),27.22),ATRIB(6)=RNORM(ATRIB(5),1.342),
   ATRIB(4)=RNORM(ATRIB(3),9.73),ATRIB(8)=RNORM(ATRIB(7),1.342),ATRIB(10)=
   RNORM(ATRIB(9),10.0);
   ACTIVITY;
   ACCUMULATE,30,30,SUM;
   ACTIVITY;
   ASSIGN,ATRIB(4)=ATRIB(4)/30.0,ATRIB(6)=ATRIB(6)/30.0,ATRIB(8)=ATRIB(8)/
   30.0,ATRIB(10)=ATRIB(10)/30.0,ATRIB(2)=ATRIB(2)/30.0,6;
   ACTIVITY,,ATRIB(2).GE.237.8;
   ACTIVITY,,ATRIB(4).GE.156.2,ZAAC;
   ACTIVITY,,ATRIB(6).GE.10.1,ZAAD;
   ACTIVITY,,ATRIB(8).GE.7.097,ZAAE;
   ACTIVITY,,ATRIB(10).GE.97.0,ZAAF;
   ACTIVITY,,,ZAAG;
   ASSIGN,ATRIB(11)=ATRIB(11)+1;
   ACTIVITY;
   COLCT(2),ATRIB(11),BREAK WARP;
   ACTIVITY;
ZAAB TERMINATE;
ZAAC ASSIGN,ATRIB(12)=ATRIB(12)+1;
   ACTIVITY;
   COLCT(4),ATRIB(12),BREAK FILL;
   ACTIVITY,,,ZAAB;
ZAAD ASSIGN,ATRIB(13)=ATRIB(13)+1;
   ACTIVITY;
```

```
    COLCT(6),ATRIB(13),TEAR WARP;
    ACTIVITY,,,ZAAB;
ZAAE ASSIGN,ATRIB(14)=ATRIB(14)+1;
    ACTIVITY;
    COLCT(8),ATRIB(14),TEAR FILL;
    ACTIVITY,,,ZAAB;
ZAAF ASSIGN,ATRIB(15)=ATRIB(15)+1;
    ACTIVITY;
    COLCT(10),ATRIB(15),SEAM;
    ACTIVITY,,,ZAAB;
ZAAG ACCUMULATE,1000,1000;
    ACTIVITY;
    ASSIGN,II=II+1;
    ACTIVITY,,,ZAAB;
    END;
```

A.2 Pre-Posture Sampling Plan

```
CREATE,.1,,,50000,1;
    ACTIVITY,,II.LT.1;
    ACTIVITY,,,ZAAH;
    ASSIGN,II=1;
    ACTIVITY;
ZAAH ASSIGN,ATRIB(1)=XX(II)*246.0,ATRIB(5)=XX(II)*10.5,ATRIB(3)=XX(II)*159.17,
    ATRIB(7)=XX(II)*7.5,ATRIB(9)=XX(II)*100.0;
    ACTIVITY;
    ASSIGN,ATRIB(2)=RNORM(ATRIB(1),27.22),ATRIB(6)=RNORM(ATRIB(5),1.342),
    ATRIB(4)=RNORM(ATRIB(3),9.73),ATRIB(8)=RNORM(ATRIB(7),1.342),ATRIB(10)=
    RNORM(ATRIB(9),10.0),ATRIB(16)=ARRAY(6,II),XX(9)=ARRAY(6,II);
    ACTIVITY;
    ACCUMULATE,ATRIB(16),ATRIB(16),SUM;
    ACTIVITY;
    ASSIGN,ATRIB(4)=ATRIB(4)/XX(9),ATRIB(6)=ATRIB(6)/XX(9),ATRIB(8)=ATRIB(8)/
    XX(9),ATRIB(10)=ATRIB(10)/XX(9),ATRIB(2)=ATRIB(2)/XX(9),6;
    ACTIVITY,,ATRIB(2).GE.ARRAY(1,II),;BRKSTRW;
    ACTIVITY,,ATRIB(4).GE.ARRAY(2,II),ZAAC;BRKSTRF;
    ACTIVITY,,ATRIB(6).GE.ARRAY(3,II),ZAAD;TRSTRW;
    ACTIVITY,,ATRIB(8).GE.ARRAY(4,II),ZAAE;TRSTRF;
    ACTIVITY,,ATRIB(10).GE.ARRAY(5,II),ZAAF;SEAMSTR;
    ACTIVITY,,,ZAAG;
    ASSIGN,ATRIB(11)=ATRIB(11)+1;
    ACTIVITY;
    COLCT(2),ATRIB(11),BREAK WARP;
    ACTIVITY;
ZAAB TERMINATE;
ZAAC ASSIGN,ATRIB(12)=ATRIB(12)+1;
    ACTIVITY;
```

```
   COLCT(4),ATRIB(12),BREAK FILL;
   ACTIVITY,,,ZAAB;
ZAAD ASSIGN,ATRIB(13)=ATRIB(13)+1;
   ACTIVITY;
   COLCT(6),ATRIB(13),TEAR WARP;
   ACTIVITY,,,ZAAB;
ZAAE ASSIGN,ATRIB(14)=ATRIB(14)+1;
   ACTIVITY;
   COLCT(8),ATRIB(14),TEAR FILL;
   ACTIVITY,,,ZAAB;
ZAAF ASSIGN,ATRIB(15)=ATRIB(15)+1;
   ACTIVITY;
   COLCT(10),ATRIB(15),SEAM;
   ACTIVITY,,,ZAAB;
ZAAG ACCUMULATE,1000,1000;
   ACTIVITY;
   ASSIGN,II=II+1;
   ACTIVITY;
   TERMINATE,1;
   END;
```

A.3 Sequential Sampling Plan

```
CREATE,.01,,,,1;
   ACTIVITY,,II.LT.1;
   ACTIVITY,,,ZAAE;
   ASSIGN,II=1;
   ACTIVITY;
ZAAE ASSIGN,ATRIB(1)=XX(II)*246;
   ACTIVITY;
   ASSIGN,ATRIB(2)=RNORM(ATRIB(1),27.22),XX(13)=XX(13)+ATRIB(2),XX(14)=XX(
   14)+1,XX(15)=29.79+XX(14)*218,XX(16)=-38.24+XX(14)*218,1;
   ACTIVITY,,XX(13).GE.XX(15);
   ACTIVITY,,XX(13).LE.XX(16),ZAAC;
   ACTIVITY,,,ZAAD;
   COLCT,XX(14),ACCEPTED;
   ACTIVITY;
ZAAB COLCT,XX(14),AVERAGE;
   ACTIVITY;
   ASSIGN,XX(13)=0,XX(14)=0,XX(15)=0,XX(16)=0;
   ACTIVITY;
   ACCUMULATE,1000,1000;
   ACTIVITY;
   ASSIGN,II=II+1;
   ACTIVITY;
   TERMINATE,1;
ZAAC COLCT,XX(14),REJECTED;
```

```
   ACTIVITY,,,ZAAB;
ZAAD TERMINATE;
   END;
```

A.4 Aggregated Sequential Sampling Plan

```
CREATE,.01,,,,1;
   ACTIVITY,,II.LT.1;
   ACTIVITY,,,ZAAE;
   ASSIGN,II=1;
   ACTIVITY;
ZAAE ASSIGN,ATRIB(1)=XX(II)*246,ATRIB(3)=XX(II)*159.17,ATRIB(5)=XX(II)*10.5,
   ATRIB(7)=XX(II)*7.5,ATRIB(9)=XX(II)*100,ATRIB(11)=XX(II)*98.17;
   ACTIVITY;
   ASSIGN,ATRIB(13)=XX(II)*98.17,ATRIB(15)=XX(II)*13.7,ATRIB(17)=XX(II)*13.7,
   ATRIB(19)=XX(II)*2.32,ATRIB(21)=XX(II)*2.32;
   ACTIVITY;
   ASSIGN,ATRIB(2)=RNORM(ATRIB(1),27.22),ATRIB(2)=ATRIB(2)-190,ATRIB(2)=
   ATRIB(2)/27.22*.0556,ATRIB(4)=RNORM(ATRIB(3),9.73),ATRIB(4)=ATRIB(4)-115,
   1;
   ACTIVITY;
   ASSIGN,ATRIB(4)=ATRIB(4)/9.73*.0556,ATRIB(6)=RNORM(ATRIB(5),1.342),ATRIB(
   6)=ATRIB(6)-10,ATRIB(6)=ATRIB(6)/1.342*.0556,1;
   ACTIVITY;
   ASSIGN,ATRIB(8)=RNORM(ATRIB(7),1.342),ATRIB(8)=ATRIB(8)-
7,ATRIB(8)=ATRIB(
   8)/1.342*.0556,ATRIB(10)=RNORM(ATRIB(9),10),ATRIB(10)=ATRIB(10)-70,1;
   ACTIVITY;

ASSIGN,ATRIB(10)=ATRIB(10)/10*.0556,ATRIB(12)=RNORM(ATRIB(11),8.68),ATRIB(
   12)=ATRIB(12)-90,ATRIB(12)=ATRIB(12)/8.68*.0556,1;
   ACTIVITY;
   ASSIGN,ATRIB(14)=RNORM(ATRIB(13),8.68),ATRIB(14)=ATRIB(14)-90,ATRIB(14)=
   ATRIB(14)/8.68*.0556,ATRIB(16)=RNORM(ATRIB(15),9.55),ATRIB(16)=20-ATRIB(
   16),1;
   ACTIVITY;
   ASSIGN,ATRIB(16)=ATRIB(16)/9.55*.0556,ATRIB(18)=RNORM(ATRIB(17),9.55),
   ATRIB(18)=20-ATRIB(18),ATRIB(18)=ATRIB(18)/9.55*.0556,1;
   ACTIVITY;
   ASSIGN,ATRIB(20)=RNORM(ATRIB(19),.29),ATRIB(20)=ATRIB(20)-1.3,ATRIB(20)=
   ATRIB(20)/.29*.25,ATRIB(22)=RNORM(ATRIB(21),.29),ATRIB(22)=ATRIB(22)-1.3,
   ATRIB(22)=ATRIB(22)/.29*.25,1;
   ACTIVITY;

ASSIGN,XX(17)=ATRIB(2)+ATRIB(4)+ATRIB(6)+ATRIB(8)+ATRIB(10)+ATRIB(12),XX(
   17)=XX(17)+XX(14)+XX(16)+XX(18)+XX(20)+XX(22),1;
   ACTIVITY;
```

```
    ASSIGN,XX(13)=XX(13)+XX(17),XX(14)=XX(14)+1,XX(15)=1.19+XX(14)*-.1441,XX(
    16)=--1.53+XX(14)*-.1441,1;
    ACTIVITY,,XX(13).GE.XX(15);
    ACTIVITY,,XX(13).LE.XX(16),ZAAC;
    ACTIVITY,,,ZAAD;
    COLCT,XX(14),ACCEPTED;
    ACTIVITY;
ZAAB COLCT,XX(14),AVERAGE;
    ACTIVITY;
    ASSIGN,XX(13)=0,XX(14)=0,XX(15)=0,XX(16)=0;
    ACTIVITY;
    ACCUMULATE,1000,1000;
    ACTIVITY;
    ASSIGN,II=II+1;
    ACTIVITY;
    TERMINATE,1;
ZAAC COLCT,XX(14),REJECTED;
    ACTIVITY,,,ZAAB;
ZAAD TERMINATE;
    END;
```

A.5 Truncated Sequential Sampling Plan

```
IMPLICIT DOUBLE PRECISION(A-H,O-Z)
      INTEGER BSWFLAG, BSFFLAG, TSWFLAG,TSFFLAG,SEAMFLAG
      INTEGER SPRYFLAG, CHEMFLAG, YR, FLAGS, I,J, YR, TESTS(12)
      INTEGER BSWS(12),BSFS(12),TSWS(12),TSFS(12),SEAMS(12)
      INTEGER SPRYS(12), H2OS(12), CHEMS(12),MASTER
      REAL  SUITRUN, DEGEN1(12),TESTR(12)
      REAL DEGEN2(12),DEGEN3(12),DEGEN4(12),DEGEN5(12),DEGEN6(12)
      REAL RNNOF,BSW,BSF,TSW,TSF,SEAM,SPRY,H2O,CHEM
      REAL
BSWSUM,BSFSUM,TSWSUM,TSFSUM,SEAMSUM,SPRYSUM,H2OSUM,CHEMSUM

      EXTERNAL RNNOF,RNSET


      DATA DEGEN1/ 1.,1.,1.,1.,1.,.998,.993,.976,.923,.784,
     + .505,.165/
      DATA DEGEN2/ .999,.998,.993,.983,.961,.921,.85,.74,.6,
     + .42,.25,.11/
      DATA DEGEN3/ .883,3859,.836,.812,.789,.766,.744,.72,.7,
     + .68,.66,.64/
      DATA DEGEN4/ .78,.751,.723,.7,.672,.65,.628,.607,.587,
     + .568,.55,.53/
      DATA DEGEN5/ .68,.654,.632,.613,.595,.58,.563,.55,.536,
     + .523,.51,.5/
```

```
      DATA DEGEN6/ .969,.952,.93,.904,.873,.838,.8,.757,.711,
     + .66,.61,.56/
      CALL RNSET(6125)

      DO 20 I=1,12
        TESTS(I)=0
        BSWS(I)=0
        BSFS(I)=0
        TSWS(I)=0
        TSFS(I)=0
        SEAMS(I)=0
        SPRYS(I)=0
        H2OS(I)=0
        CHEMS(I)=0
20    CONTINUE
      PRINT *,'TRUNC 2 RUN 1'

      DO 100 MASTER=1,1000

      SUITS=360.0
      T=0.0
      SUITRUN=30.0
      DO 30 YR=1,12

      BSWFLAG=0
      BSFFLAG=0
      TSWFLAG=0
      TSFFLAG=0
      SEAMFLAG=0
      SPRYFLAG=0
      CHEMFLAG=0
      BSWSUM=0.0
      BSFSUM=0.0
      TSWSUM=0.0
      TSFSUM=0.0
      SEAMSUM=0.0
      SPRYSUM=0.0
      H2OSUM=0.0
      CHEMSUM=0.0


        IF ((FLAGS.NE.7).AND.(T.LT.SUITRUN)) THEN
40          T=T+1.0
          TESTS(YR)=TESTS(YR)+1
          BSW=246.0*DEGEN2(YR)+RNNOF()*27.22
          BSF= 159.17*DEGEN2(YR)+RNNOF()*9.73
          TSW= 10.5*DEGEN2(YR)+RNNOF()*1.342
          TSF= 7.5*DEGEN2(YR)+RNNOF()*1.342
```

```
      SEAM= 100.0*DEGEN2(YR)+RNNOF()*10.0
      SPRY= 98.17*DEGEN2(YR)+RNNOF()*8.68
      H2O= 13.7*(2.0-DEGEN2(YR))+RNNOF()*9.55
      CHEM= 2.32*DEGEN2(YR)+RNNOF()*.29

      BSWSUM=BSWSUM+BSW
      BSFSUM=BSFSUM+BSF
      TSWSUM=TSWSUM+TSW
      TSFSUM=TSFSUM+TSF
      SEAMSUM=SEAMSUM+SEAM
      SPRYSUM=SPRYSUM+SPRY
      H2OSUM=H2OSUM+H2O
      CHEMSUM=CHEMSUM+CHEM

      BSWHI=29.79+218.0*T
      BSWLO=-38.24+218.0*T
      BSFHI=4.83+137.085*T
      BSFLO=-6.2+137.085*T
      TSWHI=8.11+10.25*T
      TSWLO=-10.41+10.25*T
      TSFHI=8.11+7.25*T
      TSFLO=-10.41+7.25*T
      SEAMHI=7.5+85.0*T
      SEAMLO=-9.63+85.0*T
      SPRYHI=20.76+94.085*T
      SPRYLO=-26.65+94.085*T
      CHEMHI=.19+1.81*T
      CHEMLO=-.24+1.81*T

    IF ((BSWSUM.GE.BSWHI).OR.(BSWSUM.LE.BSWLO)) BSWFLAG=1
    IF ((BSFSUM.GE.BSFHI).OR.(BSFSUM.LE.BSFLO)) BSFFLAG=1
    IF ((TSWSUM.GE.TSWHI).OR.(TSWSUM.LE.TSWLO)) TSWFLAG=1
    IF ((TSFSUM.GE.TSFHI).OR.(TSFSUM.LE.TSFLO)) TSFFLAG=1
    IF ((SEAMSUM.GE.SEAMHI).OR.(SEAMSUM.LE.SEAMLO)) SEAMFLAG=1
    IF ((SPRYSUM.GE.SPRYHI).OR.(SPRYSUM.LE.SPRYLO)) SPRYFLAG=1
    IF ((CHEMSUM.GE.CHEMHI).OR.(CHEMSUM.LE.CHEMLO)) CHEMFLAG=1

      FLAGS=BSWFLAG+BSFFLAG+TSWFLAG+TSFFLAG+SEAMFLAG+
C       SPRYFLAG+CHEMFLAG
      IF ((FLAGS.NE.7).AND.(T.LT.SUITRUN)) GO TO 40
    END IF


      BSWCRT=((29.79-38.24)/2.0)+218.0*T
      BSFCRT=((4.83-6.2)/2.0)+137.085*T
      TSWCRT=((8.11-10.41)/2.0)+10.25*T
      TSFCRT=((8.11-10.41)/2.0)+7.25*T
```

```
      SEAMCRT=((7.5-9.63)/2.0)+85.0*T
      SPRYCRT=((20.76-26.65)/2.0)+94.085*T
      H2OCRT=((-32.59+41.84)/2.0)+16.85*T
      CHEMCRT=((.19-.24)/2.0)+1.81*T

      IF (BSWSUM.GE.BSWCRT) BSWS(YR)=BSWS(YR)+1
      IF (BSFSUM.GE.BSFCRT) BSFS(YR)=BSFS(YR)+1
      IF (TSWSUM.GE.TSWCRT) TSWS(YR)=TSWS(YR)+1
      IF (TSFSUM.GE.TSFCRT) TSFS(YR)=TSFS(YR)+1
      IF (SEAMSUM.GE.SEAMCRT) SEAMS(YR)=SEAMS(YR)+1
      IF (SPRYSUM.GE.SPRYCRT) SPRYS(YR)=SPRYS(YR)+1
      IF (H2OSUM.LE.H2OCRT) H2OS(YR)=H2OS(YR)+1
      IF (CHEMSUM.GE.CHEMCRT) CHEMS(YR)=CHEMS(YR)+1

      SUITS=SUITS-T
      YRREAL=YR
      IF (YR.NE.12) SUITRUN=SUITS/(12.0-YRREAL)

      T=0.0
      BSWFLAG=0
      BSFFLAG=0
      TSWFLAG=0
      TSFFLAG=0
      SEAMFLAG=0
      SPRYFLAG=0
      CHEMFLAG=0
      FLAGS=0

30    CONTINUE
100   CONTINUE

      DO 50 J=1,12
       TESTR(J)=TESTS(J)/1000.0
       PRINT *,' '
       PRINT *,J
       PRINT *, 'TESTS ',TESTR(J)
       PRINT *, 'BSW ',BSWS(J)
       PRINT *, 'BSF ',BSFS(J)
       PRINT *, 'TSW ',TSWS(J)
       PRINT *, 'TSF ',TSFS(J)
       PRINT *, 'SEAM ',SEAMS(J)
       PRINT *, 'SPRAY ',SPRYS(J)
       PRINT *, 'WATER ',H2OS(J)
       PRINT *, 'CHEM ',CHEMS(J)
50     CONTINUE
      END
```

A.6 Bayesian Sampling Plan

```
IMPLICIT DOUBLE PRECISION(A-H,O-Z)
     REAL PASSES(12),REJECTS(12),TESTSIZE(12),TESTAVG(12),DEGEN1(12)
     REAL DEGEN2(12),DEGEN3(12),DEGEN4(12),DEGEN5(12),DEGEN6(12)
     REAL RNNOF
     EXTERNAL RNNOF,RNSET


     DATA DEGEN1/ 1.,1.,1.,1.,1.,.998,.993,.976,.923,.784,
    + .505,.165/
     DATA DEGEN2/ .999,.998,.993,.983,.961,.921,.85,.74,.6,
    + .42,.25,.11/
     DATA DEGEN3/ .883,3859,.836,.812,.789,.766,.744,.72,.7,
    + .68,.66,.64/
     DATA DEGEN4/ .78,.751,.723,.7,.672,.65,.628,.607,.587,
    + .568,.55,.53/
     DATA DEGEN5/ .68,.654,.632,.613,.595,.58,.563,.55,.536,
    + .523,.51,.5/
     DATA DEGEN6/ .969,.952,.93,.904,.873,.838,.8,.757,.711,
    + .66,.61,.56/

     DO 469 MASTER=1,6

      DO 440 KNT4=1,12
       PASSES(KNT4)=0.0
       REJECTS(KNT4)=0.0
       TESTSIZE(KNT4)=0.0
440    CONTINUE


     PRINT *,'Chem',MASTER
     FIRSTMN=2.32
     STDDEV=.29
     TSTMIN=1.3
     CALL RNSET(1966)

* LOOP RUNS 1000 SIMULATIONS
     DO 410 KNT1=1,100
*      PRINT *,'KNT1',KNT1
* INITIALIZE STARTING VARIABLES

       II=1
       SIG=9.9
       SDELT=.1
       DELT=.49
```

```
400     IF (II.LE.12) THEN
        CALL BAYES(SIG,SDELT,DELT,XTM,NTM)
        GOOD=0.0
        BAD=0.0

        DO 420 KNT2=1,NTM
          IF (MASTER.EQ.1) THEN
            SUITVAL=FIRSTMN*DEGEN1(II)+RNNOF()*STDDEV
          END IF
          IF (MASTER.EQ.2) THEN
            SUITVAL=FIRSTMN*DEGEN2(II)+RNNOF()*STDDEV
          END IF
          IF (MASTER.EQ.3) THEN
            SUITVAL=FIRSTMN*DEGEN3(II)+RNNOF()*STDDEV
          END IF
          IF (MASTER.EQ.4) THEN
            SUITVAL=FIRSTMN*DEGEN4(II)+RNNOF()*STDDEV
          END IF
          IF (MASTER.EQ.5) THEN
            SUITVAL=FIRSTMN*DEGEN5(II)+RNNOF()*STDDEV
          END IF
          IF (MASTER.EQ.6) THEN
            SUITVAL=FIRSTMN*DEGEN6(II)+RNNOF()*STDDEV
          END IF


          IF (SUITVAL.GE.TSTMIN) THEN
            GOOD=GOOD+1.0D0
          ELSE
            BAD=BAD+1.0D0
          END IF

420       CONTINUE

         IF (GOOD .GE. XTM) THEN
          PASSES(II)=PASSES(II)+1.0
          SIG=SIG+GOOD
          SDELT=SDELT+BAD
          DELT=(SIG/(SIG+SDELT))-.5D0
          IF (DELT .LE. 0.0) THEN
            PASSES(II)=PASSES(II)-1.0
            GO TO 415
          END IF
```

```
          TESTSIZE(II)=TESTSIZE(II)+NTM
          II=II+1
          GO TO 400
        ELSE
415        REJECTS(II)=REJECTS(II)+1.0

          TESTSIZE(II)=TESTSIZE(II)+NTM
        END IF

      ELSE
        II=1
      END IF

410   CONTINUE

* OUTPUT THE RESULTS OF SIMULATION
     DO 430 KNT3=1,12
      IF ((PASSES(KNT3)+REJECTS(KNT3)).LE.0.0) THEN
        TESTAVG(KNT3) = 0.0
      ELSE
        TESTAVG(KNT3)=TESTSIZE(KNT3)/(PASSES(KNT3)+REJECTS(KNT3))
      END IF

      PRINT *,'YEAR',KNT3
      PRINT *,'TESTSIZE: ',TESTAVG(KNT3)
      PRINT *,'PASSED: ',PASSES(KNT3)
      PRINT *,'REJECTED: ',REJECTS(KNT3)
      PRINT *,' '
430   CONTINUE
469   CONTINUE
     END



     SUBROUTINE BAYES(SGM;SDEL,DEL,XT,NT)
     IMPLICIT DOUBLE PRECISION(A-H,O-Z)
        DOUBLE PRECISION MDBETA

 13   NT=2
        ALF=.05
     BETA1=.10
     BET=1.0-BETA1
     X1=DEL
     X2=1.0

* WE START THE ALGORITHM BY INITIATING XT AS ZERO
     W1=SGM
```

```
      W2=SDEL
      A1=W1
      B1=W2
      CALL FACT1(A1,B1,SON)
      W=SON
11    XT=0.0
      WNT=NT
      W4=WNT+SDEL
      TA1=SGM
      TB1=W4
      CALL FACT2(TA1,TB1,TERS)
      PAR=TERS
      CO1=W*PAR
* THIS IS THE VALUE WHEN XT IS ZERO

* NOW WE COMPUTE THE VALUE G1 WHEN XT IS OTHER THAN ZERO
301   IXT=XT
      TOT=CO1
      IF (XT.EQ.0.0) GO TO 1001

      DO 1000 I=1,IXT
        RI=I
        P1=W1+RI
        P2=W4-RI
        TA1=P1
        TB1=P2
        CALL FACT2(TA1,TB1,TERS)
        P3=WNT+1.0
        P4=P3-RI
        P5=RI+1.0
        Z=(DGAMMA(P3))/((DGAMMA(P4))*(DGAMMA(P5)))
        P=TERS
        TOT=TOT+(P*Z*W)
1000  CONTINUE

1001  G1=TOT
* SO WE COMPUTED THE VALUE OF THE FIRST CONSTRAINT

      IF (G1.GT.ALF) GO TO 333
      IF (XT.EQ.NT) GO TO 380
      XT=XT+1.0
      GO TO 301
333   XT=XT-1.0
      IF (XT.LT.0.0) GO TO 999
* OTHERWISE WE GO AND CALCULATE G2
380   WW=W*(DEL**WNT)

* NOW COMPUTE THE VALUE WHEN XT IS ZERO, THAT IS J IS ZERO
```

```
* WHEN J IS ZERO, L IS ZERO
* WHEN J IS ZERO, M GOES FROM ZERO TO NT AND L IS ALWAYS ZERO IN THIS
CASE
* FIRST CONSIDER THE CASE WHEN M IS ZERO
      A=W1
      B=W2
      TA1=W1
      TB1=W2
      CALL FACT2(TA1,TB1,TERS)
      P1= MDBETA(X1,A,B)
      P2= MDBETA(X2,A,B)
      Y=TERS
      VALO=(P2-P1)*Y
      SUM=VALO

* NOW CONSIDER THE CASES WHERE M IS ONE TO NT
      DO 1500 M=1,NT
        A=W1
        BM=M
        BM1=WNT+1.0
        BM2=WNT-BM+1.0
        BM3=BM+1.0
        BMCOM=DGAMMA(BM1)/((DGAMMA(BM2))*(DGAMMA(BM3)))
        BFAC=(DEL**(-BM))*BMCOM
        B=W2+BM
        TA1=W1
        TB1=B
        CALL FACT2(TA1,TB1,TERS)
        P1=MDBETA(X1,A,B)
        P2=MDBETA(X2,A,B)
        Y=TERS
        VAL=(P2-P1)*Y*BFAC
        SUM=SUM+VAL
 1500  CONTINUE

      JXT=XT
      RJSUM=SUM
* IF XT IS ZERO WE HAVE ONLY THE ABOVE TERM
      IF (XT.EQ.0.0) GO TO 2001

      DO 2000 J=1,JXT
* THIS IS THE MOST OUTER SUM
        RJ=J
        RJ1=WNT+1.0
        RJ2=WNT-RJ+1.0
        RJ3=RJ+1.0
        COMBJ=(DGAMMA(RJ1))/((DGAMMA(RJ2))*(DGAMMA(RJ3)))
```

```
* NOW L IS FROM ZERO TO J.  AGAIN CONSIDER THE CASE WHERE L IS ZERO
      LP=(-1)**J
      PL=LP
* NOTE WHEN L IS ZERO, M GOES FROM ZERO TO NT-J
      LJL=NT-J
      IF (LJL.EQ.0) GO TO 2101

      DO 2100 M=1,LJL
        RRM=M
        RRM1=WNT-RJ+1.0
        RRM2=WNT-RJ-RRM+1.0
        RRM3=RRM+1.0
        RCOM=(DGAMMA(RRM1))/((DGAMMA(RRM2))*(DGAMMA(RRM3)))
        FFAC=(DEL**(-RRM))*RCOM
        A=SGM
        B=RRM+SDEL
        TA1=A
        TB1=B
        CALL FACT2(TA1,TB1,TERS)
        P1=MDBETA(X1,A,B)
        P2=MDBETA(X2,A,B)
        Y=TERS
        VALM=(P2-P1)*FFAC*Y
        VALO=VALO+VALM
 2100   CONTINUE

 2101   RLSUM=VALO*PL
* THIS IS THE VALUE WHEN L IS ZERO

* NOW WE WANT TO CONSIDER L FROM 1 TO J. THIS IS THE SECOND SUM
      DO 2500 L=1,J
        RL=L
        RL1=RJ-RL+1.0
        RL2=RL+1.0
        COMBL=(DGAMMA(RJ3))/((DGAMMA(RL1))*(DGAMMA(RL2)))
        LPL=(-1)**(J-L)
        FLP=LPL
        POWER=DEL**(-RL)
        FACL=FLP*COMBL*POWER

* NOW CONSIDER M LOOP AGAIN.  NOW M IS FROM ZERO TO NT-J FOR GIVEN L
* START WITH M = 0
        A=RL+SGM
        B=SDEL
        P1=MDBETA(X1,A,B)
        P2=MDBETA(X2,A,B)
        TA1=A
        TB1=B
```

```
        CALL FACT2(TA1,TB1,TERS)
        Y=TERS
        VAL=(P2-P1)*Y
        RMSUM=VAL
        LL=NT-J
        IF (LL.EQ.0) GO TO 3001

        DO 3000 M=1,LL
          RM=M
          RM1=WNT-RJ+1.0
          RM2=WNT-RJ-RM+1.0
          RM3=RM+1.0
          COMBM=(DGAMMA(RM1))/((DGAMMA(RM2))*(DGAMMA(RM3)))
          FACM=(DEL**(-RM))*(COMBM)
          A=RL+SGM
          B=RM+SDEL
          P1=MDBETA(X1,A,B)
          P2=MDBETA(X2,A,B)
          TA1=A
          TB1=B
          CALL FACT2(TA1,TB1,TERS)
          Y=TERS
          VAL=(P2-P1)*FACM*Y
          RMSUM=RMSUM+VAL
3000      CONTINUE

3001      RRSUM=RMSUM
* THE MOST INNER LOOP IS FINISHED

        RLSUM=(FACL*RRSUM)+RLSUM
* THIS IS THE SUM FOR L LOOP

2500    CONTINUE
* L LOOP IS FINISHED

* NOW FINISH J LOOP, THE MOST OUTER LOOP
      RJSUM=(COMBJ*RLSUM)+RJSUM
2000  CONTINUE
* SO WE EVALUATED G2

2001  G2=RJSUM*WW
    IF (G2.LE.BET) THEN
      IF (XT.LE.1.0) GO TO 999
      XT=XT-1.0
      GO TO 380
    END IF

777   IF (XT.LT.1.0) GO TO 888
```

```
      XT=XT-1.0
* CHECK G2 AGAIN
      WW=W*(DEL**WNT)

* NOW COMPUTE THE VALUE WHEN XT IS ZERO, THAT IS WHEN J IS ZERO
* WHEN J IS ZERO, L IS ZERO
* WHEN J IS ZERO, M GOES FROM ZERO TO NT AND L IS ALWAYS ZERO IN THIS
CASE
* FIRST CONSIDER THE CASE WHEN M IS ZERO
      A=W1
      B=W2
      P1=MDBETA(X1,A,B)
      P2=MDBETA(X2,A,B)
      TA1=A
      TB1=B
      CALL FACT2(TA1,TB1,TERS)
      Y=TERS
      VALO=(P2-P1)*Y
      SUM=VALO

* NOW CONSIDER THE CASES WHERE M IS ONE TO NT
      DO 1501 M=1,NT
        A=W1
        BM=M
        BM1=WNT+1.0
        BM2=WNT-BM+1.0
        BM3=BM+1.0
        BMCOM=DGAMMA(BM1)/((DGAMMA(BM2))*(DGAMMA(BM3)))
        BFAC=(DEL**(-BM))*BMCOM
        B=W2+BM
        TA1=A
        TB1=B
        CALL FACT2(TA1,TB1,TERS)
        P1=MDBETA(X1,A,B)
        P2=MDBETA(X2,A,B)
        Y=TERS
        VAL=(P2-P1)*Y*BFAC
        SUM=SUM+VAL
 1501  CONTINUE

      JXT=XT
      RJSUM=SUM
* IF XT IS ZERO, WE HAVE ONLY THE ABOVE TERM
      IF (XT.EQ.0.0) GO TO 2011

      DO 5000 J=1,JXT
* THIS IS THE MOST OUTER TERM
        RJ=J
```

```
      RJ1=WNT+1.0
      RJ2=WNT-RJ+1.0
      RJ3=RJ+1.0
      COMBJ=(DGAMMA(RJ1))/((DGAMMA(RJ2))*(DGAMMA(RJ3)))
* NOW L IS FROM ZERO TO J.  AGAIN CONSIDER THE CASE WHERE L IS ZERO
      LP=(-1)**J
      PL=LP
* NOTE WHEN L IS ZERO M GOES FROM ZERO TO NT-J
      LJL=NT-J
      IF (LJL.EQ.0) GO TO 2102

      DO 2105 M=1,LJL
        RRM=M
        RRM1=WNT-RJ+1.0
        RRM2=WNT-RJ-RRM+1.0
        RRM3=RRM+1.0
        RCOM=(DGAMMA(RRM1))/((DGAMMA(RRM2))*(DGAMMA(RRM3)))
        FFAC=(DEL**(-RRM))*RCOM
        A=SGM
        B=RRM+SDEL
        P1=MDBETA(X1,A,B)
        P2=MDBETA(X2,A,B)
        TA1=A
        TB1=B
        CALL FACT2(TA1,TB1,TERS)
        Y=TERS
        VALM=(P2-P1)*FFAC*Y
        VALO=VALO+VALM
 2105   CONTINUE

 2102   RLSUM=VALO*PL
* THIS IS THE VALUE WHEN L IS ZERO

* NOW WE WANT TO CONSIDER L FROM 1 TO J. THIS IS THE SECOND SUM
      DO 2501 L=1,J
        RL=L
        RL1=RJ-RL+1.0
        RL2=RL+1.0
        COMBL=(DGAMMA(RJ3))/((DGAMMA(RL1))*(DGAMMA(RL2)))
        LPL=(-1)**(J-L)
        FLP=LPL
        POWER=DEL**(-RL)
        FACL=FLP*COMBL*POWER

* NOW CONSIDER M LOOP AGAIN. NOW M IS FROM ZERO TO NT-J FOR GIVEN L
* START WITH M = ZERO
        A=RL+SGM
        B=SDEL
```

```
        P1=MDBETA(X1,A,B)
        P2=MDBETA(X2,A,B)
        TA1=A
        TB1=B
        CALL FACT2(TA1,TB1,TERS)
        Y=TERS
        VAL=(P2-P1)*Y
        RMSUM=VAL
        LL=NT-J
        IF (LL.EQ.0) GO TO 4001

        DO 4000 M=1,LL
          RM=M
          RM1=WNT-RJ+1.0
          RM2=WNT-RJ-RM+1.0
          RM3=RM+1.0
          COMBM=(DGAMMA(RM1))/((DGAMMA(RM2))*(DGAMMA(RM3)))
          FACM=(DEL**(-RM))*(COMBM)
          A=RL+SGM
          B=RM+SDEL
          P1=MDBETA(X1,A,B)
          P2=MDBETA(X2,A,B)
          TA1=A
          TB1=B
          CALL FACT2(TA1,TB1,TERS)
          Y=TERS
          VAL=(P2-P1)*FACM*Y
          RMSUM=RMSUM+VAL
 4000     CONTINUE

 4001     RRSUM=RMSUM
* THE MOST INNER LOOP IS FINISHED

        RLSUM=(FACL*RRSUM)+RLSUM
* THIS IS THE SUM FOR L LOOP

 2501    CONTINUE
* L LOOP IS FINISHED

* NOW FINISH J LOOP, THE MOST OUTER LOOP
      RJSUM=(COMBJ*RLSUM)+RJSUM
 5000  CONTINUE
* SO WE EVALUATED G2

 2011  G2=RJSUM*WW
* CHECK G2 NOW
     IF (G2.GE.BET) GO TO 777
     XT=XT+1.0
```

```
      GO TO 888
999   NT=NT+1
      IF (NT.GE.75) THEN
        SGM=SGM-.2
        GO TO 13
      END IF
      GO TO 11
888   RETURN
      END


      SUBROUTINE FACT1(A1,B1,SON)
      IMPLICIT DOUBLE PRECISION(A-H,O-Z)
      C=A1+B1
      IF (A1.LE.57.0.AND.C.LE.57.0) GO TO 41
      C1=C-1.0
      A2=A1-1.0
      B2=B1-1.0
      C2=A2+B2
      IB=A2+1.0
      IC=C2
      PAY=C1

      DO 42 I=IB,IC
        ZI=I
        PAY=PAY*ZI
42    CONTINUE

      PAYDA=1.0
      JA=B2

      DO 43 J=1,JA
        VJ=J
        PAYDA=PAYDA*VJ
43    CONTINUE

      SON=PAY/PAYDA
      GO TO 45
41    SON=DGAMMA(C)/((DGAMMA(A1))*(DGAMMA(B1)))
45    CONTINUE
      RETURN
      END


      SUBROUTINE FACT2(TA1,TB1,TERS)
      IMPLICIT DOUBLE PRECISION(A-H,O-Z)
```

```
      C=TA1+TB1
      IF (TA1.LE.57.0.AND.C.LE.57.0) GO TO 71
      C1=C-1.0
      A2=TA1-1.0
      B2=TB1-1.0
      C2=A2+B2
      IB=A2+1.0
      IC=C2
      PAY=C1

      DO 72 I=IB,IC
        ZI=I
        PAY=PAY*ZI
72    CONTINUE

      PAYDA=1.0
      JA=B2

      DO 73 J=1,JA
        VJ=J
        PAYDA=PAYDA*VJ
73    CONTINUE

      TERS=PAYDA/PAY
      GO TO 75
71    TERS=((DGAMMA(TA1))*(DGAMMA(TB1)))/(DGAMMA(C))
75    CONTINUE
      RETURN
      END


      DOUBLE PRECISION FUNCTION LGAMMA(XX)
      INTEGER J
         DOUBLE PRECISION COF(6),STP,HALF,ONE,FPF,X,XX,TMP,SER
      DATA COF,STP/76.18009173D0,-86.50532033D0,24.01409822D0,
     +   -1.231739516D0,.120858003D-2,-.536382D-5,2.50662827465D0/
      DATA HALF,ONE,FPF/0.5D0,1.0D0,5.5D0/
      X=XX-ONE
      TMP=X+FPF
         TMP=(X+HALF)*DLOG(TMP)-TMP
      SER=ONE
      DO 131 J=1,6
        X=X+ONE
        SER=SER+COF(J)/X
131   CONTINUE
        LGAMMA=TMP+DLOG(STP*SER)
      RETURN
      END
```

```
      DOUBLE PRECISION FUNCTION DGAMMA(XX)
      INTEGER J
        DOUBLE PRECISION COF(6),STP,HALF,ONE,FPF,X,XX,TMP,SER,LNGAMMA
      DATA COF,STP/76.18009173D0,-86.50532033D0,24.01409822D0,
     +  -1.231739516D0,.120858003D-2,-.536382D-5,2.50662827465D0/
      DATA HALF,ONE,FPF/0.5D0,1.0D0,5.5D0/
      X=XX-ONE
      TMP=X+FPF
        TMP=(X+HALF)*DLOG(TMP)-TMP
      SER=ONE
      DO 141 J=1,6
        X=X+ONE
        SER=SER+COF(J)/X
141   CONTINUE
        LNGAMMA=TMP+DLOG(STP*SER)
        DGAMMA=DEXP(LNGAMMA)
      RETURN
      END


      DOUBLE PRECISION FUNCTION MDBETA(X11,V1,W1)
        DOUBLE PRECISION BT,BT1,BT2,LGAMMA,V1,W1,BETACF,X11
      IF(X11.EQ.0..OR.X11.EQ.1.) THEN
       BT=0.0
      ELSE
       BT1=LGAMMA(V1+W1)-LGAMMA(V1)-LGAMMA(W1)
          BT2=V1*DLOG(X11)+W1*DLOG(1.0-X11)
          BT=DEXP(BT1+BT2)
      END IF
      IF(X11.LT.(V1+1.)/(V1+W1+2.)) THEN
       MDBETA=BT*BETACF(V1,W1,X11)/V1
       RETURN
      ELSE
       MDBETA=1.-BT*BETACF(W1,V1,1.-X11)/W1
       RETURN
      END IF
      END


      DOUBLE PRECISION FUNCTION BETACF(S2,T2,X21)
      INTEGER M
        DOUBLE PRECISION AM,BM,AZ,QAB,QAP,QAM,EM,TEM,S2,T2,X21
      DOUBLE PRECISION D,AP,BP,APP,BPP,AOLD,BZ
      PARAMETER(ITMAX=100,EPS=3.E-7)
      AM=1.
```

```
      BM=1.
      AZ=1.
      QAB=S2+T2
      QAP=S2+1.
      QAM=S2-1.
      BZ=1.-QAB*X21/QAP

      DO 91 M=1,ITMAX
        EM=M
        TEM=EM+EM
        D=EM*(T2-M)*X21/((QAM+TEM)*(S2+TEM))
        AP=AZ+D*AM
        BP=BZ+D*BM
        D=-(S2+EM)*(QAB+EM)*X21/((S2+TEM)*(QAP+TEM))
        APP=AP+D*AZ
        BPP=BP+D*BZ
        AOLD=AZ
        AM=AP/BPP
        BM=BP/BPP
        AZ=APP/BPP
        BZ=1.
          IF(DABS(AZ-AOLD).LT.EPS*DABS(AZ)) GO TO 95
91    CONTINUE
95    BETACF=AZ
      RETURN
      END
```

Appendix B. Simulation Results

The results of the simulations are presented in Excel spreadsheets. Each spreadsheet contains the simulations that were run for a particular sampling plan over one degradation function.

The spreadsheet contains information on the type of sampling plan run and which degradation plan was used at the top of the spreadsheet. Also a I or II after the plan indicates if it was a Condition I or a Condition II simulation. The very left column contains the name of the tests that were performed on the tests. The second and third columns give information on the starting means and standard deviations of the tests and the minimum values required for the tests and the U_1 values.

The rows of the tests give the current means of the suits, the number of suits accepted out of 1000 samples, and the average sample size of the tests. Note that in the Bayesian plans, the numbers that are accepted and rejected are given since the samples are dependent on what happened the year before, unlike the other sample plans. Also in the AF sampling plan I, the results of the Pre-Posturing results are given immediately under the results of the original sampling plan. Also note in the truncated sequential results, the average sample size is given only once since all tests used the same number of samples.

AF and Pre-Posture Sample Plan I, Weibull (.065,15)															
	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	1	1	1	1	1	0.998	0.993	0.976	0.923	0.784	0.505	0.165
Break	190	246	**Mean**	246	246	246	246	246	245.5	244.3	240.1	227.1	192.9	124.2	40.59
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	989	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	989	0	0
Break	115	159.17	**Mean**	159.2	159.2	159.2	159.2	159.2	158.9	158.1	155.3	146.9	124.8	80.38	26.26
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
Tear	10	10.5	**Mean**	10.5	10.5	10.5	10.5	10.5	10.48	10.43	10.25	9.692	8.232	5.303	1.733
Strength (W)	9.597	1.342	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	998	630	0	0	0
			# Accepted	999	998	999	1000	1000	1000	999	997	534	0	0	0
Tear	7	7.5	**Mean**	7.5	7.5	7.5	7.5	7.5	7.485	7.448	7.32	6.923	5.88	3.788	1.238
Strength (F)	6.597	1.342	**# Accepted**	999	1000	1000	1000	1000	1000	1000	1000	904	1	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	999	883	0	0	0
Seam	70	100	**Mean**	100	100	100	100	100	99.8	99.3	97.6	92.3	78.4	50.5	16.5
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
Spray	90	98.17	**Mean**	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2
Rating (UL)	84.966	8.68	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	979	4	0	0
			# Accepted	1000	1000	1000	999	1000	1000	1000	1000	977	0	0	0
Spray	90	98.17	**Mean**	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2
Rating (L)	86.64	8.68	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	973	0	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	983	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	999	953	533
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	953	533
Water (L)	20 (max)	13.7	**Mean**	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14
Adsorption	23.69	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	937	253
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	937	253
Chem (UL)	1.3	2.32	**Mean**	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	678	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	678	0
Chem (L)	1.3	2.32	**Mean**	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383
Adsorption	1.118	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	384	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	384	0

AF and Pre-Posture Sample Plan I, Weibull (.07, 7)															
	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Break	190	246	**Mean**	245.8	245.5	244.3	241.8	236.4	226.6	209.6	183	146.6	103.3	60.27	27.06
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	565	0	0	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	517	0	0	0	0
Break	115	159.17	**Mean**	159	158.9	158.1	156.5	153	146.6	135.6	118.4	94.87	66.85	39	17.51
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	999	0	0	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0	0
Tear	10	10.5	**Mean**	10.49	10.48	10.43	10.32	10.09	9.671	8.946	7.812	6.258	4.41	2.573	1.155
Strength (W)	9.597	1.342	**# Accepted**	1000	1000	1000	999	979	620	5	0	0	0	0	0
			# Accepted	999	998	999	998	979	620	1	0	0	0	0	0
Tear	7	7.5	**Mean**	7.493	7.485	7.448	7.373	7.208	6.908	6.39	5.58	4.47	3.15	1.838	0.825
Strength (F)	6.597	1.342	**# Accepted**	999	1000	1000	1000	995	881	186	0	0	0	0	0
			# Accepted	1000	1000	1000	998	995	881	115	0	0	0	0	0
Seam	70	100	**Mean**	99.9	99.8	99.3	98.3	96.1	92.1	85.2	74.4	59.6	42	24.5	11
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0	0
Spray	90	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (UL)	84.966	8.68	**# Accepted**	1000	1000	1000	1000	1000	970	323	0	0	0	0	0
			# Accepted	1000	1000	1000	999	1000	1000	195	0	0	0	0	0
Spray	90	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (L)	86.64	8.68	**# Accepted**	1000	1000	1000	1000	1000	981	69	0	0	0	0	0
			# Accepted	1000	1000	1000	1000	1000	981	20	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	999	1000	989	908	699	440
			# Accepted	1000	1000	1000	1000	1000	1000	1000	998	982	858	699	440
Water (L)	20 (max)	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	23.69	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	999	999	983	836	448	149
			# Accepted	1000	1000	1000	1000	1000	1000	1000	999	985	718	448	149
Chem (UL)	1.3	2.32	**Mean**	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	997	44	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	998	4	0	0
Chem (L)	1.3	2.32	**Mean**	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.118	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	999	0	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0

AF and Pre-Posture Sample Plan I, Weibull (.03,1.1)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.883	0.859	0.836	0.812	0.789	0.766	0.744	0.723	0.701	0.68	0.66	0.64
Break	190	246	**Mean**	217.2	211.3	205.7	199.8	194.1	188.4	183	177.9	172.4	167.3	162.4	157.4
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	999	992	913	596	205	28	3	1	0
			# Accepted	1000	1000	1000	999	992	913	522	134	1	0	1	0
Break	115	159.17	**Mean**	140.5	136.7	133.1	129.2	125.6	121.9	118.4	115.1	111.6	108.2	105.1	101.9
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	947	393	10	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	958	219	0	0	0
Tear	10	10.5	**Mean**	9.272	9.02	8.778	8.526	8.285	8.043	7.812	7.592	7.361	7.14	6.93	6.72
Strength (W)	9.597	1.342	**# Accepted**	72	6	0	0	0	0	0	0	0	0	0	0
			# Accepted	460	223	4	2	0	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	6.623	6.443	6.27	6.09	5.918	5.745	5.58	5.423	5.258	5.1	4.95	4.8
Strength (F)	6.597	1.342	**# Accepted**	549	264	86	17	1	0	0	0	0	0	0	0
			# Accepted	779	644	220	94	1	0	0	0	0	0	0	0
Seam	70	100	**Mean**	88.3	85.9	83.6	81.2	78.9	76.6	74.4	72.3	70.1	68	66	64
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	998	957	713	306	50
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	963	590	306	50
Spray	90	98.17	**Mean**	86.68	84.33	82.07	79.71	77.46	75.2	73.04	70.98	68.82	66.76	64.79	62.83
Rating (UL)	84.966	8.68	**# Accepted**	700	379	139	24	1	0	0	0	0	0	0	0
			# Accepted	931	845	303	106	1	0	0	0	0	0	0	0
Spray	90	98.17	**Mean**	86.68	84.33	82.07	79.71	77.46	75.2	73.04	70.98	68.82	66.76	64.79	62.83
Rating (L)	86.64	8.68	**# Accepted**	472	98	3	0	0	0	0	0	0	0	0	0
			# Accepted	760	496	46	1	0	0	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	15.3	15.63	15.95	16.28	16.59	16.91	17.21	17.49	17.8	18.08	18.36	18.63
Adsorption	25.537	9.55	**# Accepted**	1000	999	1000	998	1000	998	997	1000	994	993	995	992
			# Accepted	998	1000	998	999	1000	998	998	997	994	996	995	992
Water (L)	20 (max)	13.7	**Mean**	15.3	15.63	15.95	16.28	16.59	16.91	17.21	17.49	17.8	18.08	18.36	18.63
Adsorption	23.69	9.55	**# Accepted**	1000	1000	1000	999	999	1000	998	997	998	996	999	994
			# Accepted	1000	999	999	999	999	1000	999	999	1000	998	999	994
Chem(UL)	1.3	2.32	**Mean**	2.049	1.993	1.94	1.884	1.83	1.777	1.726	1.677	1.626	1.578	1.531	1.485
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Chem(L)	1.3	2.32	**Mean**	2.049	1.993	1.94	1.884	1.83	1.777	1.726	1.677	1.626	1.578	1.531	1.485
Adsorption	1.188	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000

AF and Pre-Posture Sample Plan I, Weibull (.035, .8)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.78	0.751	0.723	0.697	0.672	0.649	0.628	0.607	0.587	0.568	0.55	0.533
Break	190	246	**Mean**	191.9	184.7	177.9	171.5	165.3	159.7	154.5	149.3	144.4	139.7	135.3	131.1
Strength (W)	181.824	27.22	**# Accepted**	978	732	234	23	0	0	0	0	0	0	0	0
			# Accepted	982	867	396	86	0	0	0	0	0	0	0	0
Break	115	159.17	**Mean**	124.2	119.5	115.1	110.9	107	103.3	99.96	96.62	93.43	90.41	87.54	84.84
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	951	241	0	0	0	0	0	0	0	0
			# Accepted	1000	1000	958	408	0	0	0	0	0	0	0	0
Tear	10	10.5	**Mean**	8.19	7.886	7.592	7.319	7.056	6.815	6.594	6.374	6.164	5.964	5.775	5.597
Strength (W)	9.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted	1	0	0	0	0	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	5.85	5.633	5.423	5.228	5.04	4.868	4.71	4.553	4.403	4.26	4.125	3.998
Strength (F)	6.597	1.342	**# Accepted**	1	0	0	0	0	0	0	0	0	0	0	0
			# Accepted	124	45	0	0	0	0	0	0	0	0	0	0
Seam	70	100	**Mean**	78	75.1	72.3	69.7	67.2	64.9	62.8	60.7	58.7	56.8	55	53.3
Strength	66.997	10	**# Accepted**	1000	1000	997	934	530	126	3	0	0	0	0	0
			# Accepted	1000	1000	996	944	530	126	2	0	0	0	0	0
Spray	90	98.17	**Mean**	76.57	73.73	70.98	68.42	65.97	63.71	61.65	59.59	57.63	55.76	53.99	52.32
Rating (UL)	84.966	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted	222	83	0	0	0	0	0	0	0	0	0	0
Spray	90	98.17	**Mean**	76.57	73.73	70.98	68.42	65.97	63.71	61.65	59.59	57.63	55.76	53.99	52.32
Rating (L)	86.64	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted	8	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	16.71	17.11	17.49	17.85	18.19	18.51	18.8	19.08	19.36	19.62	19.87	20.1
Adsorption	25.537	9.55	**# Accepted**	999	997	998	993	996	984	989	986	986	978	974	960
			# Accepted	998	1000	995	992	996	984	991	983	980	970	974	960
Water (L)	20 (max)	13.7	**Mean**	16.71	17.11	17.49	17.85	18.19	18.51	18.8	19.08	19.36	19.62	19.87	20.1
Adsorption	23.69	9.55	**# Accepted**	1000	998	999	996	995	992	984	985	982	966	969	969
			# Accepted	998	995	999	993	995	992	991	989	982	962	969	969
Chem(UL)	1.3	2.32	**Mean**	1.81	1.742	1.677	1.617	1.559	1.506	1.457	1.408	1.362	1.318	1.276	1.237
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	997	994	977	944	873
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	996	970	944	873
Chem(L)	1.3	2.32	**Mean**	1.81	1.742	1.677	1.617	1.559	1.506	1.457	1.408	1.362	1.318	1.276	1.237
Adsorption	1.188	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	999	996	977	916	801
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	998	970	916	801

AF and Pre-Posture Sample Plan I, Weibull (.03,.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.679	0.654	0.632	0.613	0.595	0.578	0.563	0.549	0.536	0.523	0.511	0.5
Break	190	246	**Mean**	167	160.9	155.5	150.8	146.4	142.2	138.5	135.1	131.9	128.7	125.7	123
Strength (W)	181.824	27.22	**# Accepted**	2	0	0	0	0	0	0	0	0	0	0	0
			# Accepted	130	20	0	0	0	0	0	0	0	0	0	0
Break	115	159.17	**Mean**	108.1	104.1	100.6	97.57	94.71	92	89.61	87.38	85.32	83.25	81.34	79.59
Strength (F)	112.079	9.73	**# Accepted**	9	0	0	0	0	0	0	0	0	0	0	0
			# Accepted	229	17	0	0	0	0	0	0	0	0	0	0
Tear	10	10.5	**Mean**	7.13	6.867	6.636	6.437	6.248	6.069	5.912	5.765	5.628	5.492	5.366	5.25
Strength (W)	9.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted	0	0	0	0	0	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	5.093	4.905	4.74	4.598	4.463	4.335	4.223	4.118	4.02	3.923	3.833	3.75
Strength (F)	6.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted	1	0	0	0	0	0	0	0	0	0	0	0
Seam	70	100	**Mean**	67.9	65.4	63.2	61.3	59.5	57.8	56.3	54.9	53.6	52.3	51.1	50
Strength	66.997	10	**# Accepted**	684	192	23	0	0	0	0	0	0	0	0	0
			# Accepted	861	569	73	16	0	0	0	0	0	0	0	0
Spray	90	98.17	**Mean**	66.66	64.2	62.04	60.18	58.41	56.74	55.27	53.9	52.62	51.34	50.16	49.09
Rating (UL)	84.966	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted	1	0	0	0	0	0	0	0	0	0	0	0
Spray	90	98.17	**Mean**	66.66	64.2	62.04	60.18	58.41	56.74	55.27	53.9	52.62	51.34	50.16	49.09
Rating (L)	86.64	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted	0	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	18.1	18.44	18.74	19	19.25	19.48	19.69	19.88	20.06	20.23	20.4	20.55
Adsorption	25.537	9.55	**# Accepted**	991	989	989	983	975	970	969	967	972	963	955	952
			# Accepted	996	996	985	988	975	970	975	971	960	952	955	952
Water (L)	20 (max)	13.7	**Mean**	18.1	18.44	18.74	19	19.25	19.48	19.69	19.88	20.06	20.23	20.4	20.55
Adsorption	23.69	9.55	**# Accepted**	993	989	987	982	985	985	968	966	960	944	945	940
			# Accepted	993	990	985	978	985	985	970	961	957	918	945	940
Chem (UL)	1.3	2.32	**Mean**	1.575	1.517	1.466	1.422	1.38	1.341	1.306	1.274	1.244	1.213	1.186	1.16
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	998	994	966	926	869	813	729	644
			# Accepted	1000	1000	1000	999	998	994	968	933	812	700	729	644
Chem (L)	1.3	2.32	**Mean**	1.575	1.517	1.466	1.422	1.38	1.341	1.306	1.274	1.244	1.213	1.186	1.16
Adsorption	1.188	0.29	**# Accepted**	1000	1000	1000	1000	998	990	957	883	798	650	473	356
			# Accepted	1000	1000	1000	1000	998	990	970	881	719	473	473	356

AF and Pre-Posture Sample Plan I, Weibull (.05,2.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.969	0.952	0.93	0.904	0.873	0.838	0.799	0.757	0.711	0.664	0.614	0.564
Break	190	246	**Mean**	238.4	234.2	228.8	222.4	214.8	206.1	196.6	186.2	174.9	163.3	151	138.7
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	808	80	0	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	780	15	0	0	0
Break	115	159.17	**Mean**	154.2	151.5	148	143.9	139	133.4	127.2	120.5	113.2	105.7	97.73	89.77
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	729	0	0	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	636	0	0	0
Tear	10	10.5	**Mean**	10.17	9.996	9.765	9.492	9.167	8.799	8.39	7.949	7.466	6.972	6.447	5.922
Strength (W)	9.597	1.342	**# Accepted**	986	949	752	349	31	1	0	0	0	0	0	0
			# Accepted	986	959	804	504	31	1	0	0	0	0	0	0
Tear	7	7.5	**Mean**	7.268	7.14	6.975	6.78	6.548	6.285	5.993	5.678	5.333	4.98	4.605	4.23
Strength (F)	6.597	1.342	**# Accepted**	995	991	933	774	408	102	8	0	0	0	0	0
			# Accepted	995	986	958	834	408	102	0	0	0	0	0	0
Seam	70	100	**Mean**	96.9	95.2	93	90.4	87.3	83.8	79.9	75.7	71.1	66.4	61.4	56.4
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	988	386	1	0
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	992	194	1	0
Spray	90	98.17	**Mean**	95.13	93.46	91.3	88.75	85.7	82.27	78.44	74.31	69.8	65.18	60.28	55.37
Rating (UL)	84.966	8.68	**# Accepted**	1000	998	989	906	604	159	14	0	0	0	0	0
			# Accepted	1000	1000	989	938	604	159	1	0	0	0	0	0
Spray	90	98.17	**Mean**	95.13	93.46	91.3	88.75	85.7	82.27	78.44	74.31	69.8	65.18	60.28	55.37
Rating (L)	86.64	8.68	**# Accepted**	1000	1000	990	856	322	17	0	0	0	0	0	0
			# Accepted	1000	1000	987	877	322	17	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	14.12	14.36	14.66	15.02	15.44	15.92	16.45	17.03	17.66	18.3	18.99	19.67
Adsorption	25.537	9.55	**# Accepted**	1000	999	1000	998	1000	999	997	1000	995	991	991	975
			# Accepted	1000	1000	1000	1000	1000	999	999	998	994	996	991	975
Water (L)	20 (max)	13.7	**Mean**	14.12	14.36	14.66	15.02	15.44	15.92	16.45	17.03	17.66	18.3	18.99	19.67
Adsorption	23.69	9.55	**# Accepted**	1000	1000	1000	999	999	1000	1000	1000	999	992	994	980
			# Accepted	1000	1000	1000	1000	999	1000	1000	1000	1000	998	994	980
Chem (UL)	1.3	2.32	**Mean**	2.248	2.209	2.158	2.097	2.025	1.944	1.854	1.756	1.65	1.54	1.424	1.308
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	973
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	973
Chem (L)	1.3	2.32	**Mean**	2.248	2.209	2.158	2.097	2.025	1.944	1.854	1.756	1.65	1.54	1.424	1.308
Adsorption	1.188	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	978
			# Accepted	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	978

AF Sample Plan II, Weibull (.065,15)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16	> 4 Years Early
TEST			Degradation	1	1	1	1	1	0.998	0.993	0.976	0.923	0.784	0.505	0.165	
Break	246	246	Mean	246	246	246	246	246	245.5	244.3	240.1	227.1	192.9	124.2	40.59	
Strength (W)	190	27.22	# Accepted	949	943	951	953	950	946	916	654	16	0	0	0	14.8943
			# Accepted													
Break	159.17	159.17	Mean	159.2	159.2	159.2	159.2	159.2	158.9	158.1	155.3	146.9	124.8	80.38	26.26	
Strength (F)	115	9.73	# Accepted	940	935	949	949	958	938	841	316	0	0	0	0	16.5924
			# Accepted													
Tear	10.5	10.5	Mean	10.5	10.5	10.5	10.5	10.5	10.48	10.43	10.25	9.692	8.232	5.303	1.733	
Strength (W)	10	1.342	# Accepted	943	949	953	956	947	952	908	738	51	0	0	0	14.7154
			# Accepted													
Tear	7.5	7.5	Mean	7.5	7.5	7.5	7.5	7.5	7.485	7.448	7.32	6.923	5.88	3.788	1.238	
Strength (F)	7	1.342	# Accepted	945	948	946	934	942	931	915	823	257	0	0	0	15.2516
			# Accepted													
Seam	100	100	Mean	100	100	100	100	100	99.8	99.3	97.6	92.3	78.4	50.5	16.5	
Strength	70	10	# Accepted	945	945	949	953	941	934	892	607	5	0	0	0	15.2519
			# Accepted													
Spray	98.17	98.17	Mean	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2	
Rating (UL)	90	8.68	# Accepted	955	951	965	961	962	953	937	842	172	0	0	0	12.3582
			# Accepted													
Spray	98.17	98.17	Mean	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2	
Rating (L)	90	8.68	# Accepted	952	962	945	958	957	949	921	697	16	0	0	0	13.4546
			# Accepted													
Water (UL)	13.7	13.7	Mean	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14	
Adsorption	20 (max)	9.55	# Accepted	963	962	959	962	964	963	965	954	935	807	353	14	11.1577
			# Accepted													
Water (L)	13.7	13.7	Mean	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14	
Adsorption	20 (max)	9.55	# Accepted	953	963	962	946	962	969	952	946	889	647	73	0	11.7135
			# Accepted													
Chem (UL)	2.32	2.32	Mean	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383	
Adsorption	1.3	0.29	# Accepted	966	960	973	964	974	964	953	874	435	0	0	0	9.76787
			# Accepted													
Chem (L)	2.32	2.32	Mean	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383	
Adsorption	1.3	0.29	# Accepted	956	962	959	949	951	952	920	785	176	0	0	0	11.8035

AF Sample Plan II, Weibull (.07,7)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			Degradation	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Break	246	246	Mean	245.8	245.5	244.3	241.8	236.4	226.6	209.6	183	146.6	103.3	60.27	27.06
Strength (W)	190	27.22	# Accepted	941	932	895	790	372	10	0	0	0	0	0	0
			# Accepted												
Break	159.17	159.17	Mean	159	158.9	158.1	156.5	153	146.6	135.6	118.4	94.87	66.85	39	17.51
Strength (F)	115	9.73	# Accepted	928	916	848	540	41	0	0	0	0	0	0	0
			# Accepted												
Tear	10.5	10.5	Mean	10.49	10.48	10.43	10.32	10.09	9.671	8.946	7.812	6.258	4.41	2.573	1.155
Strength (W)	10	1.342	# Accepted	938	939	914	810	464	34	0	0	0	0	0	0
			# Accepted												
Tear	7.5	7.5	Mean	7.493	7.485	7.448	7.373	7.208	6.908	6.39	5.58	4.47	3.15	1.838	0.825
Strength (F)	7	1.342	# Accepted	941	944	914	861	667	219	5	0	0	0	0	0
			# Accepted												
Seam	100	100	Mean	99.9	99.8	99.3	98.3	96.1	92.1	85.2	74.4	59.6	42	24.5	11
Strength	70	10	# Accepted	940	935	895	764	322	4	0	0	0	0	0	0
			# Accepted												
Spray	98.17	98.17	Mean	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (UL)	90	8.68	# Accepted	951	947	937	877	669	156	0	0	0	0	0	0
			# Accepted												
Spray	98.17	98.17	Mean	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (L)	90	8.68	# Accepted	951	948	903	797	425	17	0	0	0	0	0	0
			# Accepted												
Water (UL)	13.7	13.7	Mean	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	20 (max)	9.55	# Accepted	963	962	958	956	950	929	881	743	501	217	49	8
			# Accepted												
Water (L)	13.7	13.7	Mean	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	20 (max)	9.55	# Accepted	953	962	961	930	936	892	764	527	201	21	2	0
			# Accepted												
Chem (UL)	2.32	2.32	Mean	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.3	0.29	# Accepted	966	957	955	921	771	415	38	0	0	0	0	0
			# Accepted												
Chem (L)	2.32	2.32	Mean	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.3	0.29	# Accepted	954	953	926	856	613	136	0	0	0	0	0	0

AF Sample Plan II, Weibull (.03,1.1)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.883	0.859	0.836	0.812	0.789	0.766	0.744	0.723	0.701	0.68	0.66	0.64
Break	246	246	**Mean**	217.2	211.3	205.7	199.8	194.1	188.4	183	177.9	172.4	167.3	162.4	157.4
Strength (W)	190	27.22	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Break	159.17	159.17	**Mean**	140.5	136.7	133.1	129.2	125.6	121.9	118.4	115.1	111.6	108.2	105.1	101.9
Strength (F)	115	9.73	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Tear	10.5	10.5	**Mean**	9.272	9.02	8.778	8.526	8.285	8.043	7.812	7.592	7.361	7.14	6.93	6.72
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Tear	7.5	7.5	**Mean**	6.623	6.443	6.27	6.09	5.918	5.745	5.58	5.423	5.258	5.1	4.95	4.8
Strength (F)	7	1.342	**# Accepted**	25	4	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Seam	100	100	**Mean**	88.3	85.9	83.6	81.2	78.9	76.6	74.4	72.3	70.1	68	66	64
Strength	70	10	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Spray	98.17	98.17	**Mean**	86.68	84.33	82.07	79.71	77.46	75.2	73.04	70.98	68.82	66.76	64.79	62.83
Rating (UL)	90	8.68	**# Accepted**	11	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Spray	98.17	98.17	**Mean**	86.68	84.33	82.07	79.71	77.46	75.2	73.04	70.98	68.82	66.76	64.79	62.83
Rating (L)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Water (UL)	13.7	13.7	**Mean**	15.3	15.63	15.95	16.28	16.59	16.91	17.21	17.49	17.8	18.08	18.36	18.63
Adsorption	20 (max)	9.55	**# Accepted**	893	884	866	823	813	779	759	714	692	663	622	560
			# Accepted												
Water (L)	13.7	13.7	**Mean**	15.3	15.63	15.95	16.28	16.59	16.91	17.21	17.49	17.8	18.08	18.36	18.63
Adsorption	20 (max)	9.55	**# Accepted**	825	788	768	709	655	571	540	472	407	376	333	280
			# Accepted												
Chem(UL)	2.32	2.32	**Mean**	2.049	1.993	1.94	1.884	1.83	1.777	1.726	1.677	1.626	1.578	1.531	1.485
Adsorption	1.3	0.29	**# Accepted**	122	41	14	0	0	0	0	0	0	0	0	0
			# Accepted												
Chem(L)	2.32	2.32	**Mean**	2.049	1.993	1.94	1.884	1.83	1.777	1.726	1.677	1.626	1.578	1.531	1.485
Adsorption	1.3	0.29	**# Accepted**	4	0	0	0	0	0	0	0	0	0	0	0

AF Sample Plan II, Weibull (.035,.8)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.78	0.751	0.723	0.697	0.672	0.649	0.628	0.607	0.587	0.568	0.55	0.533
Break	246	246	**Mean**	191.9	184.7	177.9	171.5	165.3	159.7	154.5	149.3	144.4	139.7	135.3	131.1
Strength (W)	190	27.22	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Break	159.17	159.17	**Mean**	124.2	119.5	115.1	110.9	107	103.3	99.96	96.62	93.43	90.41	87.54	84.84
Strength (F)	115	9.73	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Tear	10.5	10.5	**Mean**	8.19	7.886	7.592	7.319	7.056	6.815	6.594	6.374	6.164	5.964	5.775	5.597
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Tear	7.5	7.5	**Mean**	5.85	5.633	5.423	5.228	5.04	4.868	4.71	4.553	4.403	4.26	4.125	3.998
Strength (F)	7	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Seam	100	100	**Mean**	78	75.1	72.3	69.7	67.2	64.9	62.8	60.7	58.7	56.8	55	53.3
Strength	70	10	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Spray	98.17	98.17	**Mean**	76.57	73.73	70.98	68.42	65.97	63.71	61.65	59.59	57.63	55.76	53.99	52.32
Rating (UL)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Spray	98.17	98.17	**Mean**	76.57	73.73	70.98	68.42	65.97	63.71	61.65	59.59	57.63	55.76	53.99	52.32
Rating (L)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Water (UL)	13.7	13.7	**Mean**	16.71	17.11	17.49	17.85	18.19	18.51	18.8	19.08	19.36	19.62	19.87	20.1
Adsorption	20 (max)	9.55	**# Accepted**	787	765	716	668	653	613	571	520	484	443	426	379
			# Accepted												
Water (L)	13.7	13.7	**Mean**	16.71	17.11	17.49	17.85	18.19	18.51	18.8	19.08	19.36	19.62	19.87	20.1
Adsorption	20 (max)	9.55	**# Accepted**	615	559	499	420	366	295	260	196	184	160	129	97
			# Accepted												
Chem(UL)	2.32	2.32	**Mean**	1.81	1.742	1.677	1.617	1.559	1.506	1.457	1.408	1.362	1.318	1.276	1.237
Adsorption	1.3	0.29	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Accepted												
Chem(L)	2.32	2.32	**Mean**	1.81	1.742	1.677	1.617	1.559	1.506	1.457	1.408	1.362	1.318	1.276	1.237
Adsorption	1.3	0.29	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0

AF Sample Plan II, Weibull (.03,.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.679	0.654	0.632	0.613	0.595	0.578	0.563	0.549	0.536	0.523	0.511	0.5
Break	246	246	**Mean**	167	160.9	155.5	150.8	146.4	142.2	138.5	135.1	131.9	128.7	125.7	123
Strength (W)	190	27.22	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Break	159.17	159.17	**Mean**	108.1	104.1	100.6	97.57	94.71	92	89.61	87.38	85.32	83.25	81.34	79.59
Strength (F)	115	9.73	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Tear	10.5	10.5	**Mean**	7.13	6.867	6.636	6.437	6.248	6.069	5.912	5.765	5.628	5.492	5.366	5.25
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	5.093	4.905	4.74	4.598	4.463	4.335	4.223	4.118	4.02	3.923	3.833	3.75
Strength (F)	7	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Seam	100	100	**Mean**	67.9	65.4	63.2	61.3	59.5	57.8	56.3	54.9	53.6	52.3	51.1	50
Strength	70	10	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Spray	98.17	98.17	**Mean**	66.66	64.2	62.04	60.18	58.41	56.74	55.27	53.9	52.62	51.34	50.16	49.09
Rating (UL)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Spray	98.17	98.17	**Mean**	66.66	64.2	62.04	60.18	58.41	56.74	55.27	53.9	52.62	51.34	50.16	49.09
Rating (L)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	13.7	13.7	**Mean**	18.1	18.44	18.74	19	19.25	19.48	19.69	19.88	20.06	20.23	20.4	20.55
Adsorption	20 (max)	9.55	**# Accepted**	643	595	579	527	526	471	441	419	390	358	363	331
Water (L)	13.7	13.7	**Mean**	18.1	18.44	18.74	19	19.25	19.48	19.69	19.88	20.06	20.23	20.4	20.55
Adsorption	20 (max)	9.55	**# Accepted**	354	310	284	210	203	154	139	96	109	92	80	63
Chem(UL)	2.32	2.32	**Mean**	1.575	1.517	1.466	1.422	1.38	1.341	1.306	1.274	1.244	1.213	1.186	1.16
Adsorption	1.3	0.29	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Chem(L)	2.32	2.32	**Mean**	1.575	1.517	1.466	1.422	1.38	1.341	1.306	1.274	1.244	1.213	1.186	1.16
Adsorption	1.3	0.29	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0

AF Sample Plan II, Weibull (.05,2.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.969	0.952	0.93	0.904	0.873	0.838	0.799	0.757	0.711	0.664	0.614	0.564
Break	246	246	**Mean**	238.4	234.2	228.8	222.4	214.8	206.1	196.6	186.2	174.9	163.3	151	138.7
Strength (W)	190	27.22	**# Accepted**	549	238	41	1	0	0	0	0	0	0	0	0
Break	159.17	159.17	**Mean**	154.2	151.5	148	143.9	139	133.4	127.2	120.5	113.2	105.7	97.73	89.77
Strength (F)	115	9.73	**# Accepted**	113	8	0	0	0	0	0	0	0	0	0	0
Tear	10.5	10.5	**Mean**	10.17	9.996	9.765	9.492	9.167	8.799	8.39	7.949	7.466	6.972	6.447	5.922
Strength (W)	10	1.342	**# Accepted**	609	321	87	5	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	7.268	7.14	6.975	6.78	6.548	6.285	5.993	5.678	5.333	4.98	4.605	4.23
Strength (F)	7	1.342	**# Accepted**	752	593	298	99	17	0	0	0	0	0	0	0
Seam	100	100	**Mean**	96.9	95.2	93	90.4	87.3	83.8	79.9	75.7	71.1	66.4	61.4	56.4
Strength	70	10	**# Accepted**	473	169	19	0	0	0	0	0	0	0	0	0
Spray	98.17	98.17	**Mean**	95.13	93.46	91.3	88.75	85.7	82.27	78.44	74.31	69.8	65.18	60.28	55.37
Rating (UL)	90	8.68	**# Accepted**	733	540	257	43	2	0	0	0	0	0	0	0
Spray	98.17	98.17	**Mean**	95.13	93.46	91.3	88.75	85.7	82.27	78.44	74.31	69.8	65.18	60.28	55.37
Rating (L)	90	8.68	**# Accepted**	514	232	31	2	0	0	0	0	0	0	0	0
Water (UL)	13.7	13.7	**Mean**	14.12	14.36	14.66	15.02	15.44	15.92	16.45	17.03	17.66	18.3	18.99	19.67
Adsorption	20 (max)	9.55	**# Accepted**	950	943	936	910	898	872	825	762	713	630	546	429
Water (L)	13.7	13.7	**Mean**	14.12	14.36	14.66	15.02	15.44	15.92	16.45	17.03	17.66	18.3	18.99	19.67
Adsorption	20 (max)	9.55	**# Accepted**	932	928	914	859	823	741	665	556	431	344	227	139
Chem(UL)	2.32	2.32	**Mean**	2.248	2.209	2.158	2.097	2.025	1.944	1.854	1.756	1.65	1.54	1.424	1.308
Adsorption	1.3	0.29	**# Accepted**	846	739	509	289	68	11	2	0	0	0	0	0
Chem(L)	2.32	2.32	**Mean**	2.248	2.209	2.158	2.097	2.025	1.944	1.854	1.756	1.65	1.54	1.424	1.308
Adsorption	1.3	0.29	**# Accepted**	708	488	200	47	4	0	0	0	0	0	0	0

Sequential Sample Plan I, Weibull (.065,15)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	1	1	1	1	1	0.998	0.993	0.976	0.923	0.784	0.505	0.165
Break	190	246	**Mean**	246	246	246	246	246	245.5	244.3	240.1	227.1	192.9	124.2	40.59
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	995	0	0
			# Sampled	3.52	3.55	3.49	3.5	3.45	3.56	3.57	3.78	4.93	25.1	4.26	0
Break	115	159.17	**Mean**	159.2	159.2	159.2	159.2	159.2	158.9	158.1	155.3	146.9	124.8	80.38	26.26
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
			# Sampled	1.17	1.14	1.17	1.17	1.17	1.18	1.16	1.25	1.61	3.7	2.08	0
Tear	10	10.5	**Mean**	10.5	10.5	10.5	10.5	10.5	10.48	10.43	10.25	9.692	8.232	5.303	1.733
Strength (W)	9.597	1.342	**# Accepted**	1000	1000	1000	1000	1000	1000	991	996	381	0	0	0
			# Sampled	12.4	12.1	12.1	12.3	12.1	12.4	13.6	18.6	53.9	7.56	0	0
Tear	7	7.5	**Mean**	7.5	7.5	7.5	7.5	7.5	7.485	7.448	7.32	6.923	5.88	3.788	1.238
Strength (F)	6.597	1.342	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	859	0	0	0
			# Sampled	18.9	18.8	18.5	18.7	18.8	19.3	20.3	26.02	86.5	16.5	0	0
Seam	70	100	**Mean**	100	100	100	100	100	99.8	99.3	97.6	92.3	78.4	50.5	16.5
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
			# Sampled	2.57	2.57	2.58	2.54	2.57	2.57	2.58	2.75	3.27	7.21	5.28	0
Spray	90	98.17	**Mean**	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2
Rating (UL)	84.966	8.68	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	983	0	0	0
			# Sampled	4.43	4.46	4.45	4.34	4.44	4.45	4.72	5.7	14.5	5.28	0	0
Water (UL)	20 (max)	13.7	**Mean**	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	590	0
			# Sampled	31.1	31.1	31.1	31.2	30.8	31.1	31.9	32.9	36.5	55.8	615	58.7
Chem (UL)	1.3	2.32	**Mean**	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1	0
			# Sampled	3.31	3.34	3.32	3.3	3.29	3.31	3.35	3.44	3.88	5.93	40.8	4.78

Sequential Sample Plan I, Weibull (.07, 7)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Break	190	246	**Mean**	245.8	245.5	244.3	241.8	236.4	226.6	209.6	183	146.6	103.3	60.27	27.06
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	244	0	0	0	0
			# Sampled	3.53	3.56	3.58	3.74	4.05	4.96	8.16	58.1	6.53	0	0	0
Break	115	159.17	**Mean**	159	158.9	158.1	156.5	153	146.6	135.6	118.4	94.87	66.85	39	17.51
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	999	0	0	0	0
			# Sampled	1.18	1.15	1.19	1.24	1.39	1.64	2.16	7.01	3.38	0	0	0
Tear	10	10.5	**Mean**	10.49	10.48	10.43	10.32	10.09	9.671	8.946	7.812	6.258	4.41	2.573	1.155
Strength (W)	9.597	1.342	**# Accepted**	1000	1000	1000	998	990	325	0	0	0	0	0	0
			# Sampled	12.6	12.4	13.7	15.7	26	53.4	13.9	0	0	0	0	0
Tear	7	7.5	**Mean**	7.493	7.485	7.448	7.373	7.208	6.908	6.39	5.58	4.47	3.15	1.838	0.825
Strength (F)	6.597	1.342	**# Accepted**	1000	1000	1000	1000	998	820	0	0	0	0	0	0
			# Sampled	19.2	19.2	20.1	22.8	33.7	96.1	36.8	0	0	0	0	0
Seam	70	100	**Mean**	99.9	99.8	99.3	98.3	96.1	92.1	85.2	74.4	59.6	42	24.5	11
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0	0
			# Sampled	2.58	2.58	2.64	2.66	2.89	3.27	4.5	11.8	10.6	0	0	0
Spray	90	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (UL)	84.966	8.68	**# Accepted**	1000	1000	1000	1000	1000	981	6	0	0	0	0	0
			# Sampled	4.47	4.53	4.75	5.2	6.73.	16.02	13.2	3.92	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	999	7	0	0
			# Sampled	31.2	31.2	31.6	32.3	33.4	37.2	44.5	63.5	167	236	75.5	0
Chem (UL)	1.3	2.32	**Mean**	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0
			# Sampled	3.31	3.35	3.36	3.41	3.55	3.95	4.68	7.09	27	13.7	0	0

Sequential Sample Plan I, Weibull (.03,1.1)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
Test			**Degradation**	0.883	0.859	0.836	0.812	0.789	0.766	0.744	0.723	0.701	0.68	0.66	0.64
Break	190	246	**Mean**	217.2	211.3	205.7	199.8	194.1	188.4	183	177.9	172.4	167.3	162.4	157.4
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	999	897	244	18	1	0	0	0
			# Sampled	6.34	7.69	9.66	13.7	21.6	49.2	56.3	32.3	18.8	13.8	0	0
Break	115	159.17	**Mean**	140.5	136.7	133.1	129.2	125.6	121.9	118.4	115.1	111.6	108.2	105.1	101.9
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	974	414	27	2	1
			# Sampled	1.91	2.1	2.43	2.83	3.54	4.57	7.16	14.2	24.8	13.5	7.62	5.41
Tear	10	10.5	**Mean**	9.272	9.02	8.778	8.526	8.285	8.043	7.812	7.592	7.361	7.14	6.93	6.72
Strength (W)	9.597	1.342	**# Accepted**	12	1	1	0	0	0	0	0	0	0	0	0
			# Sampled	22.7	15.4	11.7	9.49	0	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	6.623	6.443	6.27	6.09	5.918	5.745	5.58	5.423	5.258	5.1	4.95	4.8
Strength (F)	6.597	1.342	**# Accepted**	61	3	0	0	0	0	0	0	0	0	0	0
			# Sampled	67	39.9	28.4	0	0	0	0	0	0	0	0	0
Seam	70	100	**Mean**	88.3	85.9	83.6	81.2	78.9	76.6	74.4	72.3	70.1	68	66	64
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	962	429	41	1
			# Sampled	3.84	4.35	4.92	5.68	6.85	8.76	11.8	17.2	36.3	63.3	37.6	21
Spray	90	98.17	**Mean**	86.68	84.33	82.07	79.71	77.46	75.2	73.04	70.98	68.82	66.76	64.79	62.83
Rating (UL)	84.966	8.68	**# Accepted**	252	19	0	0	0	0	0	0	0	0	0	0
			# Sampled	26.8	15.1	9.59	0	0	0	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	15.3	15.63	15.95	16.28	16.59	16.91	17.21	17.49	17.8	18.08	18.36	18.63
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
			# Sampled	40.4	43.5	46.1	49	54.6	58.2	65.3	70.2	79.3	86	95.9	115
Chem (UL)	1.3	2.32	**Mean**	2.049	1.993	1.94	1.884	1.83	1.777	1.726	1.677	1.626	1.578	1.531	1.485
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
			# Sampled	4.28	4.64	4.95	5.34	5.77	6.37	7.06	7.86	8.88	10.4	11.8	14.7

Sequential Sample Plan I, Weibull (.035, .8)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.78	0.751	0.723	0.697	0.672	0.649	0.628	0.607	0.587	0.568	0.55	0.533
Break	190	246	**Mean**	191.9	184.7	177.9	171.5	165.3	159.7	154.5	149.3	144.4	139.7	135.3	131.1
Strength (W)	181.824	27.22	**# Accepted**	979	466	20	1	0	0	0	0	0	0	0	0
			# Sampled	28.4	62.6	31.5	17.3	12.4	0	0	0	0	0	0	0
Break	115	159.17	**Mean**	124.2	119.5	115.1	110.9	107	103.3	99.96	96.62	93.43	90.41	87.54	84.84
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	965	266	8	0	0	0	0	0	0	0
			# Sampled	3.87	6.19	13.7	22.7	10.5	6.24	0	0	0	0	0	0
Tear	10	10.5	**Mean**	8.19	7.886	7.592	7.319	7.056	6.815	6.594	6.374	6.164	5.964	5.775	5.597
Strength (W)	9.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	7.36	0	0	0	0	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	5.85	5.633	5.423	5.228	5.04	4.868	4.71	4.553	4.403	4.26	4.125	3.998
Strength (F)	6.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	16.1	0	0	0	0	0	0	0	0	0	0	0
Seam	70	100	**Mean**	78	75.1	72.3	69.7	67.2	64.9	62.8	60.7	58.7	56.8	55	53.3
Strength	66.997	10	**# Accepted**	1000	1000	1000	930	185	5	0	0	0	0	0	0
			# Sampled	7.36	10.5	17.7	41.2	53.4	25.5	16.2	0	0	0	0	0
Spray	90	98.17	**Mean**	76.57	73.73	70.98	68.42	65.97	63.71	61.65	59.59	57.63	55.76	53.99	52.32
Rating (UL)	84.966	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	5.05	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	16.71	17.11	17.49	17.85	18.19	18.51	18.8	19.08	19.36	19.62	19.87	20.1
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	999	1000	1000	999	998	996	970	933
			# Sampled	55.5	61.7	68.7	79.9	92	106	123	148	185	231	320	450
Chem (UL)	1.3	2.32	**Mean**	1.81	1.742	1.677	1.617	1.559	1.506	1.457	1.408	1.362	1.318	1.276	1.237
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	987	717	98
			# Sampled	6.08	6.85	7.81	9.06	10.9	13.3	16.4	22.6	33.1	62.7	133	107

Sequential Sample Plan I, Weibull (.03,.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
Test			**Degradation**	0.679	0.654	0.632	0.613	0.595	0.578	0.563	0.549	0.536	0.523	0.511	0.5
Break	190	246	**Mean**	167	160.9	155.5	150.8	146.4	142.2	138.5	135.1	131.9	128.7	125.7	123
Strength (W)	181.824	27.22	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	13.2	0	0	0	0	0	0	0	0	0	0	0
Break	115	159.17	**Mean**	108.1	104.1	100.6	97.57	94.71	92	89.61	87.38	85.32	83.25	81.34	79.59
Strength (F)	112.079	9.73	**# Accepted**	28	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	12.4	6.95	0	0	0	0	0	0	0	0	0	0
Tear	10	10.5	**Mean**	7.13	6.867	6.636	6.437	6.248	6.069	5.912	5.765	5.628	5.492	5.366	5.25
Strength (W)	9.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	4.59	0	0	0	0	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	5.093	4.905	4.74	4.598	4.463	4.335	4.223	4.118	4.02	3.923	3.833	3.75
Strength (F)	6.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	9.27	0	0	0	0	0	0	0	0	0	0	0
Seam	70	100	**Mean**	67.9	65.4	63.2	61.3	59.5	57.8	56.3	54.9	53.6	52.3	51.1	50
Strength	66.997	10	**# Accepted**	404	19	2	0	0	0	0	0	0	0	0	0
			# Sampled	61.6	29.6	17.4	13.2	0	0	0	0	0	0	0	0
Spray	90	98.17	**Mean**	66.66	64.2	62.04	60.18	58.41	56.74	55.27	53.9	52.62	51.34	50.16	49.09
Rating (UL)	84.966	8.68	**# Accepted**	252	19	0	0	0	0	0	0	0	0	0	0
			# Sampled	26.8	15.1	9.59	0	0	0	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	18.1	18.44	18.74	19	19.25	19.48	19.69	19.88	20.06	20.23	20.4	20.55
Adsorption	25.537	9.55	**# Accepted**	1000	1000	999	1000	998	996	988	979	932	839	696	529
			# Sampled	86.4	99.5	119	142	167	205	251	321	414	505	598	646
Chem (UL)	1.3	2.32	**Mean**	1.575	1.517	1.466	1.422	1.38	1.341	1.306	1.274	1.244	1.213	1.186	1.16
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	998	974	675	145	25	3	0
			# Sampled	10.4	12.6	15.9	20.3	27.8	42.7	78.1	132	122	71.1	46.6	36

Sequential Sample Plan I, Weibull (.05,2.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.969	0.952	0.93	0.904	0.873	0.838	0.799	0.757	0.711	0.664	0.614	0.564
Break	190	246	**Mean**	238.4	234.2	228.8	222.4	214.8	206.1	196.6	186.2	174.9	163.3	151	138.7
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	676	1	0	0	0
			# Sampled	3.93	4.26	4.72	5.42	6.79	9.51	17.3	61.2	23.2	11.4	0	0
Break	115	159.17	**Mean**	154.2	151.5	148	143.9	139	133.4	127.2	120.5	113.2	105.7	97.73	89.77
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	999	787	2	0	0
			# Sampled	1.31	1.39	1.56	1.76	1.97	2.35	3.19	5.42	22.1	8.39	4.01	0
Tear	10	10.5	**Mean**	10.17	9.996	9.765	9.492	9.167	8.799	8.39	7.949	7.466	6.972	6.447	5.922
Strength (W)	9.597	1.342	**# Accepted**	994	961	575	66	0	0	0	0	0	0	0	0
			# Sampled	21.5	33.4	57.3	37.2	18.9	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	7.268	7.14	6.975	6.78	6.548	6.285	5.993	5.678	5.333	4.98	4.605	4.23
Strength (F)	6.597	1.342	**# Accepted**	1000	997	934	378	24	0	0	0	0	0	0	0
			# Sampled	28.6	39.7	74.5	108	53.2	29.3	0	0	0	0	0	0
Seam	70	100	**Mean**	96.9	95.2	93	90.4	87.3	83.8	79.9	75.7	71.1	66.4	61.4	56.4
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	992	63	0	0
			# Sampled	2.8	2.96	3.22	3.53	3.99	4.86	6.3	9.77	24.6	41.2	13.3	0
Spray	90	98.17	**Mean**	95.13	93.46	91.3	88.75	85.7	82.27	78.44	74.31	69.8	65.18	60.28	55.37
Rating (UL)	84.966	8.68	**# Accepted**	1000	1000	994	823	95	2	0	0	0	0	0	0
			# Sampled	6.17	7.97	12	27.2	22.1	9.76	5.97	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	14.12	14.36	14.66	15.02	15.44	15.92	16.45	17.03	17.66	18.3	18.99	19.67
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	987
			# Sampled	32.9	34.6	36	38.5	41.4	46.4	51.8	61.7	74.8	97.3	134	252
Chem (UL)	1.3	2.32	**Mean**	2.248	2.209	2.158	2.097	2.025	1.944	1.854	1.756	1.65	1.54	1.424	1.308
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	972
			# Sampled	3.5	3.66	3.81	4.05	4.43	4.9	5.53	6.62	8.41	11.5	20	74.7

Sequential Sample Plan II, Weibull (.065,15)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	1	1	1	1	1	0.998	0.993	0.976	0.923	0.784	0.505	0.165
Break	246	246	**Mean**	246	246	246	246	246	245.5	244.3	240.1	227.1	192.9	124.2	40.59
Strength (W)	190	27.22	**# Accepted**	980	980	989	985	989	975	975	965	808	36	0	0
			# Sampled	1.86	1.93	1.98	1.89	1.86	1.91	1.98	2.26	3.12	2.26	1.03	0
Break	159.17	159.17	**Mean**	159.2	159.2	159.2	159.2	159.2	158.9	158.1	155.3	146.9	124.8	80.38	26.26
Strength (F)	115	9.73	**# Accepted**	999	998	996	998	999	998	994	995	933	46	0	0
			# Sampled	1.05	1.04	1.04	1.04	1.05	1.04	1.05	1.07	1.32	1.29	1	0
Tear	10.5	10.5	**Mean**	10.5	10.5	10.5	10.5	10.5	10.48	10.43	10.25	9.692	8.232	5.303	1.733
Strength (W)	10	1.342	**# Accepted**	950	963	957	952	947	964	896	532	2	0	0	0
			# Sampled	33.1	33.3	33.4	32.6	33.5	34.8	39.4	57.3	20.4	5.88	0	0
Tear	7.5	7.5	**Mean**	7.5	7.5	7.5	7.5	7.5	7.485	7.448	7.32	6.923	5.88	3.788	1.238
Strength (F)	7	1.342	**# Accepted**	950	963	957	952	947	958	928	721	44	0	0	0
			# Sampled	33.1	33.3	33.4	32.6	33.5	33.7	37.9	53.6	32.2	8.48	0	0
Seam	100	100	**Mean**	100	100	100	100	100	99.8	99.3	97.6	92.3	78.4	50.5	16.5
Strength	70	10	**# Accepted**	992	987	994	995	993	992	990	977	898	155	0	0
			# Sampled	1.29	1.23	1.28	1.32	1.29	1.28	1.28	1.37	1.86	1.98	1.01	0
Spray	98.17	98.17	**Mean**	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2
Rating (UL)	90	8.68	**# Accepted**	967	968	961	974	979	971	944	834	75	0	0	0
			# Sampled	6.39	6.18	6.02	6.25	6.33	6.6	6.97	9.53	7.98	1.02	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14
Adsorption	20	9.55	**# Accepted**	964	965	968	961	962	974	958	954	901	589	52	0
			# Sampled	10.9	11.4	11.3	11.2	11.4	11.6	11.6	11.8	13.8	20.4	12.6	5.98
Chem(UL)	2.32	2.32	**Mean**	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383
Adsorption	1.3	0.29	**# Accepted**	997	993	994	997	997	993	993	990	964	534	5	0
			# Sampled	1.17	1.13	1.16	1.17	1.15	1.17	1.14	1.2	1.4	2.03	1.09	1

Sequential Sample Plan II, Weibull (.07, 7)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Break	246	246	**Mean**	245.8	245.5	244.3	241.8	236.4	226.6	209.6	183	146.6	103.3	60.27	27.06
Strength (W)	190	27.22	**# Accepted**	980	978	984	968	936	781	303	9	0	0	0	0
			# Sampled	1.87	1.94	2.05	2.1	2.33	3.22	3.32	1.75	1	0	0	0
Break	159.17	159.17	**Mean**	159	158.9	158.1	156.5	153	146.6	135.6	118.4	94.87	66.85	39	17.51
Strength (F)	115	9.73	**# Accepted**	999	998	994	998	983	914	414	9	0	0	0	0
			# Sampled	1.05	1.04	1.05	1.08	1.14	1.38	1.75	1.11	1	0	0	0
Tear	10.5	10.5	**Mean**	10.49	10.48	10.43	10.32	10.09	9.671	8.946	7.812	6.258	4.41	2.573	1.155
Strength (W)	10	1.342	**# Accepted**	946	946	895	716	180	4	0	0	0	0	0	0
			# Sampled	34.1	34.6	41.3	53.4	48	19.7	12	0	0	0	0	0
Tear	7.5	7.5	**Mean**	7.493	7.485	7.448	7.373	7.208	6.908	6.39	5.58	4.47	3.15	1.838	0.825
Strength (F)	7	1.342	**# Accepted**	954	952	916	831	425	45	0	0	0	0	0	0
			# Sampled	34.2	34.4	39.2	47.6	57.2	31.1	20.2	0	0	0	0	0
Seam	100	100	**Mean**	99.9	99.8	99.3	98.3	96.1	92.1	85.2	74.4	59.6	42	24.5	11
Strength	70	10	**# Accepted**	992	987	990	983	970	905	558	61	2	0	0	0
			# Sampled	1.3	1.25	1.3	1.38	1.52	1.86	2.36	1.57	1.06	1	0	0
Spray	98.17	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (UL)	90	8.68	**# Accepted**	961	960	946	889	583	81	0	0	0	0	0	0
			# Sampled	6.43	6.4	6.97	8.33	11.7	7.58	3.36	0	0	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	20	9.55	**# Accepted**	964	964	966	953	938	908	794	483	119	18	2	0
			# Sampled	11	11.5	11.6	11.7	12.9	15.1	17.1	20.7	15.5	10.2	6.83	5.69
Chem(UL)	2.32	2.32	**Mean**	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.3	0.29	**# Accepted**	997	993	995	993	985	958	859	338	21	2	0	0
			# Sampled	1.18	1.13	1.17	1.2	1.27	1.42	1.8	1.95	1.29	1.02	1	0

Sequential Sample Plan II, Weibull (.03,1.1)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.883	0.859	0.836	0.812	0.789	0.766	0.744	0.723	0.701	0.68	0.66	0.64
Break	246	246	**Mean**	217.2	211.3	205.7	199.8	194.1	188.4	183	177.9	172.4	167.3	162.4	157.4
Strength (W)	190	27.22	**# Accepted**	506	309	172	107	61	25	10	8	5	3	2	0
			# Sampled	3.65	3.34	3.21	2.6	2.32	2.08	1.74	1.64	1.48	1.38	1.27	1.26
Break	159.17	159.17	**Mean**	140.5	136.7	133.1	129.2	125.6	121.9	118.4	115.1	111.6	108.2	105.1	101.9
Strength (F)	115	9.73	**# Accepted**	715	506	288	128	53	22	8	1	0	0	0	0
			# Sampled	1.61	1.81	1.63	1.43	1.29	1.18	1.09	1.05	1.03	0	0	0
Tear	10.5	10.5	**Mean**	9.272	9.02	8.778	8.526	8.285	8.043	7.812	7.592	7.361	7.14	6.93	6.72
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	11.5	0	0	0	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	6.623	6.443	6.27	6.09	5.918	5.745	5.58	5.423	5.258	5.1	4.95	4.8
Strength (F)	7	1.342	**# Accepted**	6	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	17.7	14	0	0	0	0	0	0	0	0	0	0
Seam	100	100	**Mean**	88.3	85.9	83.6	81.2	78.9	76.6	74.4	72.3	70.1	68	66	64
Strength	70	10	**# Accepted**	744	587	401	265	161	102	54	31	17	8	7	3
			# Sampled	2.12	2.31	2.29	2.3	2.04	1.78	1.61	1.48	1.39	1.25	1.19	1.13
Spray	98.17	98.17	**Mean**	86.68	84.33	82.07	79.71	77.46	75.2	73.04	70.98	68.82	66.76	64.79	62.83
Rating (UL)	90	8.68	**# Accepted**	3	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	4.57	3.44	0	0	0	0	0	0	0	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	15.3	15.63	15.95	16.28	16.59	16.91	17.21	17.49	17.8	18.08	18.36	18.63
Adsorption	20	9.55	**# Accepted**	848	812	754	679	640	558	468	440	377	279	229	199
			# Sampled	15.5	18	18.8	19.6	19.5	19.2	2.07	19.6	18.9	18.9	18.1	16.7
Chem(UL)	2.32	2.32	**Mean**	2.049	1.993	1.94	1.884	1.83	1.777	1.726	1.677	1.626	1.578	1.531	1.485
Adsorption	1.3	0.29	**# Accepted**	905	874	767	676	577	442	322	247	189	111	80	61
			# Sampled	1.59	1.75	1.86	2.03	2.09	2.08	2.04	1.95	1.86	1.62	1.59	1.46

Sequential Sample Plan II, Weibull (.035, .8)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
			Degradation	0.78	0.751	0.723	0.697	0.672	0.649	0.628	0.607	0.587	0.568	0.55	0.533
Break	246	246	**Mean**	191.9	184.7	177.9	171.5	165.3	159.7	154.5	149.3	144.4	139.7	135.3	131.1
Strength (W)	190	27.22	**# Accepted**	37	20	6	2	2	0	0	0	0	0	0	0
			# Sampled	2.18	1.85	1.59	1.42	1.31	1.25	0	0	0	0	0	0
Break	159.17	159.17	**Mean**	124.2	119.5	115.1	110.9	107	103.3	99.96	96.62	93.43	90.41	87.54	84.84
Strength (F)	115	9.73	**# Accepted**	39	13	1	1	0	0	0	0	0	0	0	0
			# Sampled	1.25	1.12	1.06	1.02	1	0	0	0	0	0	0	0
Tear	10.5	10.5	**Mean**	8.19	7.886	7.592	7.319	7.056	6.815	6.594	6.374	6.164	5.964	5.775	5.597
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	5.69	0	0	0	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	5.85	5.633	5.423	5.228	5.04	4.868	4.71	4.553	4.403	4.26	4.125	3.998
Strength (F)	7	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	8.2	0	0	0	0	0	0	0	0	0	0	0
Seam	100	100	**Mean**	78	75.1	72.3	69.7	67.2	64.9	62.8	60.7	58.7	56.8	55	53.3
Strength	70	10	**# Accepted**	130	72	25	9	9	2	0	0	0	0	0	0
			# Sampled	1.97	1.65	1.45	1.3	1.22	1.15	1.11	0	0	0	0	0
Spray	98.17	98.17	**Mean**	76.57	73.73	70.98	68.42	65.97	63.71	61.65	59.59	57.63	55.76	53.99	52.32
Rating (UL)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	2.12	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	16.71	17.11	17.49	17.85	18.19	18.51	18.8	19.08	19.36	19.62	19.87	20.1
Adsorption	20	9.55	**# Accepted**	602	498	408	323	289	213	171	160	140	97	79	54
			# Sampled	19.1	21	19.9	20.2	18.8	18	17.6	16.2	15	14.5	13.5	13.4
Chem(UL)	2.32	2.32	**Mean**	1.81	1.742	1.677	1.617	1.559	1.506	1.457	1.408	1.362	1.318	1.276	1.237
Adsorption	1.3	0.29	**# Accepted**	527	375	226	153	101	57	45	31	27	11	4	3
			# Sampled	2.07	2.06	1.89	1.79	1.67	1.52	1.39	1.32	1.26	1.2	1.18	1.12

Sequential Sample Plan II, Weibull (.03,.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
			Degradation	0.679	0.654	0.632	0.613	0.595	0.578	0.563	0.549	0.536	0.523	0.511	0.5
Break	246	246	**Mean**	167	160.9	155.5	150.8	146.4	142.2	138.5	135.1	131.9	128.7	125.7	123
Strength (W)	190	27.22	**# Accepted**	4	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	1.36	1.25	0	0	0	0	0	0	0	0	0	0
Break	159.17	159.17	**Mean**	.	104.1	100.6	97.57	94.71	92	89.61	87.38	85.32	83.25	81.34	79.59
Strength (F)	115	9.73	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	1.01	1	0	0	0	0	0	0	0	0	0	0
Tear	10.5	10.5	**Mean**	7.13	6.867	6.636	6.437	6.248	6.069	5.912	5.765	5.628	5.492	5.366	5.25
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	3.94	0	0	0	0	0	0	0	0	0	0	2.6
Tear	7.5	7.5	**Mean**	5.093	4.905	4.74	4.598	4.463	4.335	4.223	4.118	4.02	3.923	3.833	3.75
Strength (F)	7	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	5.48	0	0	0	0	0	0	0	0	0	0	0
Seam	100	100	**Mean**	67.9	65.4	63.2	61.3	59.5	57.8	56.3	54.9	53.6	52.3	51.1	50
Strength	70	10	**# Accepted**	8	3	0	0	0	0	0	0	0	0	0	0
			# Sampled	1.25	1.17	1.12	0	0	0	0	0	0	0	0	0
Spray	98.17	98.17	**Mean**	66.66	64.2	62.04	60.18	58.41	56.74	55.27	53.9	52.62	51.34	50.16	49.09
Rating (UL)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	1.47	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	18.1	18.44	18.74	19	19.25	19.48	19.69	19.88	20.06	20.23	20.4	20.55
Adsorption	20	9.55	**# Accepted**	300	215	181	148	134	120	102	72	64	69	60	41
			# Sampled	19	19	16.9	16.6	15.7	15.1	13.7	13.8	13.7	13	12.7	12
Chem (UL)	2.32	2.32	**Mean**	1.575	1.517	1.466	1.422	1.38	1.341	1.306	1.274	1.244	1.213	1.186	1.16
Adsorption	1.3	0.29	**# Accepted**	118	69	43	26	19	16	9	7	6	8	3	2
			# Sampled	1.67	1.53	1.44	1.31	1.28	1.2	1.21	1.16	1.13	1.12	1.09	1.09

Sequential Sample Plan II, Weibull (.05,2.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
			Degradation	0.969	0.952	0.93	0.904	0.873	0.838	0.799	0.757	0.711	0.664	0.614	0.564
Break	246	246	**Mean**	238.4	234.2	228.8	222.4	214.8	206.1	196.6	186.2	174.9	163.3	151	138.7
Strength (W)	190	27.22	**# Accepted**	949	915	819	684	429	194	69	23	10	0	0	0
			# Sampled	2.26	2.64	3.04	3.43	3.61	3.27	2.4	1.9	1.55	1.33	0	0
Break	159.17	159.17	**Mean**	154.2	151.5	148	143.9	139	133.4	127.2	120.5	113.2	105.7	97.73	89.77
Strength (F)	115	9.73	**# Accepted**	994	979	945	840	604	291	84	13	0	0	0	0
			# Sampled	1.12	1.16	1.29	1.46	1.66	1.68	1.37	1.15	1.03	1	0	0
Tear	10.5	10.5	**Mean**	10.17	9.996	9.765	9.492	9.167	8.799	8.39	7.949	7.466	6.972	6.447	5.922
Strength (W)	10	1.342	**# Accepted**	339	70	12	0	0	0	0	0	0	0	0	0
			# Sampled	53.5	37.7	22.6	15	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	7.268	7.14	6.975	6.78	6.548	6.285	5.993	5.678	5.333	4.98	4.605	4.23
Strength (F)	7	1.342	**# Accepted**	591	253	64	5	1	0	0	0	0	0	0	0
			# Sampled	55.3	51.2	35.8	23.1	16.2	12	0	0	0	0	0	0
Seam	100	100	**Mean**	96.9	95.2	93	90.4	87.3	83.8	79.9	75.7	71.1	66.4	61.4	56.4
Strength	70	10	**# Accepted**	975	961	921	837	705	442	215	87	17	0	1	0
			# Sampled	1.46	1.51	1.75	2.04	2.36	2.31	2.09	1.66	1.43	1.24	1.08	1.03
Spray	98.17	98.17	**Mean**	95.13	93.46	91.3	88.75	85.7	82.27	78.44	74.31	69.8	65.18	60.28	55.37
Rating (UL)	90	8.68	**# Accepted**	714	430	145	24	2	0	0	0	0	0	0	0
			# Sampled	10.1	10.7	8.87	5.8	4.01	3.03	0	0	0	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	14.12	14.36	14.66	15.02	15.44	15.92	16.45	17.03	17.66	18.3	18.99	19.67
Adsorption	20	9.55	**# Accepted**	953	918	926	874	831	774	658	507	399	272	136	83
			# Sampled	12.2	13.2	14.1	15.2	17.1	18.8	18.8	21.2	19.9	18.4	17	13.8
Chem (UL)	2.32	2.32	**Mean**	2.248	2.209	2.158	2.097	2.025	1.944	1.854	1.756	1.65	1.54	1.424	1.308
Adsorption	1.3	0.29	**# Accepted**	990	981	975	939	888	800	630	387	201	92	24	11
			# Sampled	1.26	1.25	1.37	1.5	1.65	1.87	2.1	2.06	1.88	1.61	1.38	1.19

Truncated Sequential Sample Plan I, Weibull (.065,15)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	1	1	1	1	1	0.998	0.993	0.976	0.923	0.784	0.505	0.165
Break	190	246	**Mean**	246	246	246	246	246	245.5	244.3	240.1	227.1	192.9	124.2	40.59
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	979	0	0
			# Sampled	19.18	18.88	19.57	19.65	19.88	20.58	21.92	26.82	45.67	26.35	39.23	4.75
Break	115	159.17	**Mean**	159.2	159.2	159.2	159.2	159.2	158.9	158.1	155.3	146.9	124.8	80.38	26.26
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
Tear	10	10.5	**Mean**	10.5	10.5	10.5	10.5	10.5	10.48	10.43	10.25	9.692	8.232	5.303	1.733
Strength (W)	9.597	1.342	**# Accepted**	1000	999	998	1000	999	1000	1000	995	403	0	0	0
Tear	7	7.5	**Mean**	7.5	7.5	7.5	7.5	7.5	7.485	7.448	7.32	6.923	5.88	3.788	1.238
Strength (F)	6.597	1.342	**# Accepted**	997	998	999	1000	1000	1000	1000	994	737	0	0	0
Seam	70	100	**Mean**	100	100	100	100	100	99.8	99.3	97.6	92.3	78.4	50.5	16.5
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
Spray	90	98.17	**Mean**	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2
Rating (UL)	84.966	8.68	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	992	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	999	1000	1000	994	704	635
Chem(UL)	1.3	2.32	**Mean**	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	12	0

Truncated Sequential Sample Plan I, Weibull (.07, 7)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Break	190	246	**Mean**	245.8	245.5	244.3	241.8	236.4	226.6	209.6	183	146.6	103.3	60.27	27.06
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	297	0	0	0	0
			# Sampled	19.57	19.73	20.95	23.57	29.07	34.9	29.39	31.5	23.62	13.53	6.04	4.23
Break	115	159.17	**Mean**	159	158.9	158.1	156.5	153	146.6	135.6	118.4	94.87	66.85	39	17.51
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0	0
Tear	10	10.5	**Mean**	10.49	10.48	10.43	10.32	10.09	9.671	8.946	7.812	6.258	4.41	2.573	1.155
Strength (W)	9.597	1.342	**# Accepted**	999	1000	1000	996	946	396	0	0	0	0	0	0
Tear	7	7.5	**Mean**	7.493	7.485	7.448	7.373	7.208	6.908	6.39	5.58	4.47	3.15	1.838	0.825
Strength (F)	6.597	1.342	**# Accepted**	998	998	997	994	973	745	26	0	0	0	0	0
Seam	70	100	**Mean**	99.9	99.8	99.3	98.3	96.1	92.1	85.2	74.4	59.6	42	24.5	11
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0	0
Spray	90	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (UL)	84.966	8.68	**# Accepted**	1000	1000	1000	1000	1000	977	3	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	25.537	9.55	**# Accepted**	1000	999	1000	1000	1000	1000	998	994	907	666	642	631
Chem(UL)	1.3	2.32	**Mean**	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	997	0	0	0

Truncated Sequential Sample Plan I, Weibull (.03,1.1)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.883	0.859	0.836	0.812	0.789	0.766	0.744	0.723	0.701	0.68	0.66	0.64
Break	190	246	**Mean**	217.2	211.3	205.7	199.8	194.1	188.4	183	177.9	172.4	167.3	162.4	157.4
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	984	808	352	41	5	0	0	0
			# Sampled	29.52	27.34	25.98	22.23	23.52	29.78	32.68	29.34	33.39	36.59	30.91	22.56
Break	115	159.17	**Mean**	140.5	136.7	133.1	129.2	125.6	121.9	118.4	115.1	111.6	108.2	105.1	101.9
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	999	942	381	11	0	0
Tear	10	10.5	**Mean**	9.272	9.02	8.778	8.526	8.285	8.043	7.812	7.592	7.361	7.14	6.93	6.72
Strength (W)	9.597	1.342	**# Accepted**	34	8	0	0	0	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	6.623	6.443	6.27	6.09	5.918	5.745	5.58	5.423	5.258	5.1	4.95	4.8
Strength (F)	6.597	1.342	**# Accepted**	294	89	14	0	0	0	0	0	0	0	0	0
Seam	70	100	**Mean**	88.3	85.9	83.6	81.2	78.9	76.6	74.4	72.3	70.1	68	66	64
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	995	886	472	96	4
Spray	90	98.17	**Mean**	86.68	84.33	82.07	79.71	77.46	75.2	73.04	70.98	68.82	66.76	64.79	62.83
Rating (UL)	84.966	8.68	**# Accepted**	290	127	0	0	0	0	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	15.3	15.63	15.95	16.28	16.59	16.91	17.21	17.49	17.8	18.08	18.36	18.63
Adsorption	25.537	9.55	**# Accepted**	999	1000	1000	995	997	997	995	983	987	978	952	935
Chem (UL)	1.3	2.32	**Mean**	2.049	1.993	1.94	1.884	1.83	1.777	1.726	1.677	1.626	1.578	1.531	1.485
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000

Truncated Sequential Sample Plan I, Weibull (.035, .8)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16	> 4 Years Early
TEST			**Degradation**	0.78	0.751	0.723	0.697	0.672	0.649	0.628	0.607	0.587	0.568	0.55	0.533	
Break	190	246	**Mean**	191.9	184.7	177.9	171.5	165.3	159.7	154.5	149.3	144.4	139.7	135.3	131.1	
Strength (W)	181.824	27.22	**# Accepted**	949	531	104	7	0	0	0	0	0	0	0	0	0
			# Sampled	23.52	27.91	26.88	28.4	28.51	23.5	19.91	22.09	28.66	37.18	44.07	45.09	
Break	115	159.17	**Mean**	124.2	119.5	115.1	110.9	107	103.3	99.96	96.62	93.43	90.41	87.54	84.84	
Strength (F)	112.079	9.73		1000	1000	967	390	2	0	0	0	0	0	0	0	0
Tear	10	10.5	**Mean**	8.19	7.886	7.592	7.319	7.056	6.815	6.594	6.374	6.164	5.964	5.775	5.597	
Strength (W)	9.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	5.85	5.633	5.423	5.228	5.04	4.868	4.71	4.553	4.403	4.26	4.125	3.998	
Strength (F)	6.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0	0
Seam	70	100	**Mean**	78	75.1	72.3	69.7	67.2	64.9	62.8	60.7	58.7	56.8	55	53.3	
Strength	66.997	10	**# Accepted**	1000	1000	989	871	355	46	4	0	0	0	0	0	0
Spray	90	98.17	**Mean**	76.57	73.73	70.98	68.42	65.97	63.71	61.65	59.59	57.63	55.76	53.99	52.32	
Rating (UL)	84.966	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	16.71	17.11	17.49	17.85	18.19	18.51	18.8	19.08	19.36	19.62	19.87	20.1	
Adsorption	25.537	9.55	**# Accepted**	996	996	989	983	971	931	925	910	911	837	824	750	19.3547
Chem (UL)	1.3	2.32	**Mean**	1.81	1.742	1.677	1.617	1.559	1.506	1.457	1.408	1.362	1.318	1.276	1.237	
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	999	979	897	647	251	0

Truncated Sequential Sample Plan I, Weibull (.03,.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.679	0.654	0.632	0.613	0.595	0.578	0.563	0.549	0.536	0.523	0.511	0.5
Break	190	246	**Mean**	167	160.9	155.5	150.8	146.4	142.2	138.5	135.1	131.9	128.7	125.7	123
Strength (W)	181.824	27.22	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	27.73	24.16	20.07	20.78	24.8	29.3	33.14	34.88	35.52	34.8	33.29	31.15
Break	115	159.17	**Mean**	108.1	104.1	100.6	97.57	94.71	92	89.61	87.38	85.32	83.25	81.34	79.59
Strength (F)	112.079	9.73	**# Accepted**	23	0	0	0	0	0	0	0	0	0	0	0
Tear	10	10.5	**Mean**	7.13	6.867	6.636	6.437	6.248	6.069	5.912	5.765	5.628	5.492	5.366	5.25
Strength (W)	9.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	5.093	4.905	4.74	4.598	4.463	4.335	4.223	4.118	4.02	3.923	3.833	3.75
Strength (F)	6.597	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Seam	70	100	**Mean**	67.9	65.4	63.2	61.3	59.5	57.8	56.3	54.9	53.6	52.3	51.1	50
Strength	66.997	10	**# Accepted**	503	83	4	0	0	0	0	0	0	0	0	0
Spray	90	98.17	**Mean**	66.66	64.2	62.04	60.18	58.41	56.74	55.27	53.9	52.62	51.34	50.16	49.09
Rating (UL)	84.966	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	18.1	18.44	18.74	19	19.25	19.48	19.69	19.88	20.06	20.23	20.4	20.55
Adsorption	25.537	9.55	**# Accepted**	974	955	933	909	902	887	833	819	772	747	745	711
Chem(UL)	1.3	2.32	**Mean**	1.575	1.517	1.466	1.422	1.38	1.341	1.306	1.274	1.244	1.213	1.186	1.16
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	995	971	855	669	391	194	64	20

Truncated Sequential Sample Plan I, Weibull (.05,2.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.969	0.952	0.93	0.904	0.873	0.838	0.799	0.757	0.711	0.664	0.614	0.564
Break	190	246	**Mean**	238.4	234.2	228.8	222.4	214.8	206.1	196.6	186.2	174.9	163.3	151	138.7
Strength (W)	181.824	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	993	680	27	0	0	0
			# Sampled	25.18	28.57	30.42	30.72	29.83	25.24	22.04	28.95	29.24	28.02	21.58	48.34
Break	115	159.17	**Mean**	154.2	151.5	148	143.9	139	133.4	127.2	120.5	113.2	105.7	97.73	89.77
Strength (F)	112.079	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	763	1	0	0
Tear	10	10.5	**Mean**	10.17	9.996	9.765	9.492	9.167	8.799	8.39	7.949	7.466	6.972	6.447	5.922
Strength (W)	9.597	1.342	**# Accepted**	969	870	586	185	15	0	0	0	0	0	0	0
Tear	7	7.5	**Mean**	7.268	7.14	6.975	6.78	6.548	6.285	5.993	5.678	5.333	4.98	4.605	4.23
Strength (F)	6.597	1.342	**# Accepted**	982	931	780	546	169	26	1	0	0	0	0	0
Seam	70	100	**Mean**	96.9	95.2	93	90.4	87.3	83.8	79.9	75.7	71.1	66.4	61.4	56.4
Strength	66.997	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	.976	107	0	0
Spray	90	98.17	**Mean**	95.13	93.46	91.3	88.75	85.7	82.27	78.44	74.31	69.8	65.18	60.28	55.37
Rating (UL)	84.966	8.68	**# Accepted**	1000	1000	996	743	106	0	0	0	0	0	0	0
Water (UL)	20 (max)	13.7	**Mean**	14.12	14.36	14.66	15.02	15.44	15.92	16.45	17.03	17.66	18.3	18.99	19.67
Adsorption	25.537	9.55	**# Accepted**	1000	1000	1000	1000	1000	1000	997	995	986	967	916	829
Chem(UL)	1.3	2.32	**Mean**	2.248	2.209	2.158	2.097	2.025	1.944	1.854	1.756	1.65	1.54	1.424	1.308
Adsorption	1.132	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	844

Bayesian Sample Plan, Weibull (.065,15)															
	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	1	1	1	1	1	0.998	0.993	0.976	0.923	0.784	0.505	0.165
Break	246	246	**Mean**	246	246	246	246	246	245.5	244.3	240.1	227.1	192.9	124.2	40.59
Strength (W)	190	27.22	**# Accepted**	100	98	98	98	98	98	97	97	96	38	0	0
			# Rejected	0	2	0	0	0	0	1	0	1	58	38	0
			# Sampled	6	4.42	4.58	4.43	4.53	4.66	4.73	5.24	8.27	8.76	14.5	0
Break	159.17	159.17	**Mean**	159.2	159.2	159.2	159.2	159.2	158.9	158.1	155.3	146.9	124.8	80.38	26.26
Strength (F)	115	9.73	**# Accepted**	100	100	100	100	100	100	100	100	100	89	0	0
			# Rejected	0	0	0	0	0	0	0	0	0	11	89	0
			# Sampled	4	4	4	4	4	4	4	4	4	4	4.85	0
Tear	10.5	10.5	**Mean**	10.5	10.5	10.5	10.5	10.5	10.48	10.43	10.25	9.692	8.232	5.303	1.733
Strength (W)	10	1.342	**# Accepted**	97	97	92	89	85	82	77	70	24	0	0	0
			# Rejected	3	0	5	3	4	3	5	7	46	24	0	0
			# Sampled	15	18.68	28.33	29.99	31.57	35.08	38.91	43.53	48.73	24.88	0	0
Tear	7.5	7.5	**Mean**	7.5	7.5	7.5	7.5	7.5	7.485	7.448	7.32	6.923	5.88	3.788	1.238
Strength (F)	7	1.342	**# Accepted**	95	94	92	90	88	86	82	73	41	1	0	0
			# Rejected	5	1	2	2	2	2	4	9	32	40	1	0
			# Sampled	15	18.47	27.35	29.41	31.37	34.94	38.45	42.74	48.62	33.12	2	0
Seam	100	100	**Mean**	100	100	100	100	100	99.8	99.3	97.6	92.3	78.4	50.5	16.5
Strength	70	10	**# Accepted**	100	100	100	100	100	100	100	100	100	87	0	0
			# Rejected	0	0	0	0	0	0	0	0	0	13	87	0
			# Sampled	4	4	4	4	4	4	4	4.04	4.08	4.12	5.9	0
Spray	98.17	98.17	**Mean**	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2
Rating (UL)	90	8.68	**# Accepted**	100	99	98	96	93	90	89	88	36	0	0	0
			# Rejected	0	1	1	2	3	3	1	1	52	36	0	0
			# Sampled	9	10.24	10.72	12.5	18.61	19.71	20.02	21	21.86	22.72	0	0
Water (UL)	13.7	13.7	**Mean**	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14
Adsorption	20 (max)	9.55	**# Accepted**												
			# Rejected												
			# Sampled												
Chem (UL)	2.32	2.32	**Mean**	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383
Adsorption	1.3	0.29	**# Accepted**	100	100	100	100	100	100	100	100	100	99	9	0
			# Rejected	0	0	0	0	0	0	0	0	0	1	90	9
			# Sampled	4	4	4	4	4	4.02	4.02	4.02	4.02	4.48	4.3	5.78

Bayesian Sample Plan, Weibull (.07,7)															
	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Break	246	246	**Mean**	245.8	245.5	244.3	241.8	236.4	226.6	209.6	183	146.6	103.3	60.27	27.06
Strength (W)	190	27.22	**# Accepted**	100	100	99	99	98	95	75	14	9.14	0	0	0
			# Rejected	0	0	1	0	1	3	20	61	0	0	0	0
			# Sampled	6	4.35	4.51	4.52	4.64	4.82	5.18	6.89	14	0	0	0
Break	159.17	159.17	**Mean**	159	158.9	158.1	156.5	153	146.6	135.6	118.4	94.87	66.85	39	17.51
Strength (F)	115	9.73	**# Accepted**	100	100	100	100	100	100	100	52	0	0	0	0
			# Rejected	0	0	0	0	0	0	0	48	52	0	0	0
			# Sampled	4	4	4	4	4	4	4.02	4.08	5.58	0	0	0
Tear	10.5	10.5	**Mean**	10.49	10.48	10.43	10.32	10.09	9.671	8.946	7.812	6.258	4.41	2.573	1.155
Strength (W)	10	1.342	**# Accepted**	95	95	88	83	68	26	0	0	0	0	0	0
			# Rejected	5	0	7	5	15	42	26	0	0	0	0	0
			# Sampled	15	18.35	27.14	30.78	32.74	36.71	37.04	0	0	0	0	0
Tear	7.5	7.5	**Mean**	7.493	7.485	7.448	7.373	7.208	6.908	6.39	5.58	4.47	3.15	1.838	0.825
Strength (F)	7	1.342	**# Accepted**	94	94	88	86	80	46	7	0	0	0	0	0
			# Rejected	6	0	6	2	6	34	39	7	0	0	0	0
			# Sampled	15	18.82	28.69	30.52	32.22	35.94	39.24	32.71	0	0	0	0
Seam	100	100	**Mean**	99.9	99.8	99.3	98.3	96.1	92.1	85.2	74.4	59.6	42	24.5	11
Strength	70	10	**# Accepted**	100	100	100	100	100	100	99	64	0	0	0	0
			# Rejected	0	0	0	0	0	0	1	35	64	0	0	0
			# Sampled	4	4	4.06	4.06	4.06	4.1	4.18	4.45	5.44	0	0	0
Spray	98.17	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (UL)	90	8.68	**# Accepted**	99	99	99	96	73	35	0	0	0	0	0	0
			# Rejected	1	0	0	3	23	38	35	0	0	0	0	0
			# Sampled	9	10.06	10.17	12.61	18.79	23.44	27.14	0	0	0	0	0
Water (UL)	13.7	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	20 (max)	9.55	**# Accepted**												
			# Rejected												
			# Sampled												
Chem (UL)	2.32	2.32	**Mean**	2.318	2.315	2.304	2.32	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.3	0.29	**# Accepted**	100	100	100	100	100	100	100	97	56	0	0	0
			# Rejected	0	0	0	0	0	0	0	3	41	56	0	0
			# Sampled	4	4	4	4	4	4	4.02	4.1	4.53	5.73	0	0

Bayesian Sample Plan, Weibull (.03,1.1)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.883	0.859	0.836	0.812	0.789	0.766	0.744	0.723	0.701	0.68	0.66	0.64
Break	246	246	**Mean**	217.2	211.3	205.7	199.8	194.1	188.4	183	177.9	172.4	167.3	162.4	157.4
Strength (W)	190	27.22	**# Accepted**	96	96	79	61	44	20	5	34.2	0	0	0	0
			# Rejected	4	0	17	18	17	24	15	0	0	0	0	0
			# Sampled	6	6.11	5.91	7.01	8.61	18.14	25.8	5	0	0	0	0
Break	159.17	159.17	**Mean**	140.5	136.7	133.1	129.2	125.6	121.9	118.4	115.1	111.6	108.2	105.1	101.9
Strength (F)	115	9.73	**# Accepted**	100	100	100	97	93	76	51	20	1	0	0	0
			# Rejected	0	0	0	3	4	17	25	31	19	1	0	0
			# Sampled	4	4.06	4.06	4.24	4.6	5.28	6.3	7.69	15.7	7	0	0
Tear	10.5	10.5	**Mean**	9.272	9.02	8.778	8.526	8.285	8.043	7.812	7.592	7.361	7.14	6.93	6.72
Strength (W)	10	1.342	**# Accepted**	8	8	0	0	0	0	0	0	0	0	0	0
			# Rejected	92	0	8	0	0	0	0	0	0	0	0	0
			# Sampled	15	21.25	28.25	0	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	6.623	6.443	6.27	6.09	5.918	5.745	5.58	5.423	5.258	5.1	4.95	4.8
Strength (F)	7	1.342	**# Accepted**	44	44	3	0	0	0	0	0	0	0	0	0
			# Rejected	56	0	41	3	0	0	0	0	0	0	0	0
			# Sampled	15	21.27	26.05	25.67	0	0	0	0	0	0	0	0
Seam	100	100	**Mean**	88.3	85.9	83.6	81.2	78.9	76.6	74.4	72.3	70.1	68	66	64
Strength	70	10	**# Accepted**	99	99	99	94	88	76	64	41	12	3	1	0
			# Rejected	1	0	0	5	6	12	12	23	29	9	2	1
			# Sampled	4	4.45	4.45	4.74	5.49	6.22	7.29	10.05	19.32	25.25	29	31
Spray	98.17	98.17	**Mean**	86.68	84.33	82.07	79.71	77.46	75.2	73.04	70.98	68.82	66.76	64.79	62.83
Rating (UL)	90	8.68	**# Accepted**	40	40	0	0	0	0	0	0	0	0	0	0
			# Rejected	60	0	40	0	0	0	0	0	0	0	0	0
			# Sampled	9	17	11.3	0	0	0	0	0	0	0	0	0
Water (UL)	13.7	13.7	**Mean**	15.3	15.63	15.95	16.28	16.59	16.91	17.21	17.49	17.8	18.08	18.36	18.63
Adsorption	20 (max)	9.55	**# Accepted**												
			# Rejected												
			# Sampled												
Chem (UL)	2.32	2.32	**Mean**	2.049	1.993	1.94	2.32	1.83	1.777	1.726	1.677	1.626	1.578	1.531	1.485
Adsorption	1.3	0.29	**# Accepted**	100	100	99	98	98	96	95	91	87	81	69	58
			# Rejected	0	0	1	1	0	2	1	4	4	6	12	11
			# Sampled	4	4.03	4.03	4.04	4.18	4.43	4.7	5	5.35	8.43	12.67	12.54

Bayesian Sample Plan, Weibull (.035,.8)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.78	0.751	0.723	0.697	0.672	0.649	0.628	0.607	0.587	0.568	0.55	0.533
Break	246	246	**Mean**	191.9	184.7	177.9	171.5	165.3	159.7	154.5	149.3	144.4	139.7	135.3	131.1
Strength (W)	190	27.22	**# Accepted**	41	14	5	1	0	0	0	0	0	0	0	0
			# Rejected	59	27	9	4	1	0	0	0	0	0	0	0
			# Sampled	6	7.44	12.43	17	12	0	0	0	0	0	0	0
Break	159.17	159.17	**Mean**	124.2	119.5	115.1	110.9	107	103.3	99.96	96.62	93.43	90.41	87.54	84.84
Strength (F)	115	9.73	**# Accepted**	86	68	29	5	0	0	0	0	0	0	0	0
			# Rejected	14	18	39	24	5	0	0	0	0	0	0	0
			# Sampled	4	5.53	7.24	9.34	16.2	0	0	0	0	0	0	0
Tear	10.5	10.5	**Mean**	8.19	7.886	7.592	7.319	7.056	6.815	6.594	6.374	6.164	5.964	5.775	5.597
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Rejected	100	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	15	0	0	0	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	5.85	5.633	5.423	5.228	5.04	4.868	4.71	4.553	4.403	4.26	4.125	3.998
Strength (F)	7	1.342	**# Accepted**	2	0	0	0	0	0	0	0	0	0	0	0
			# Rejected	98	2	0	0	0	0	0	0	0	0	0	0
			# Sampled	15	22	0	0	0	0	0	0	0	0	0	0
Seam	100	100	**Mean**	78	75.1	72.3	69.7	67.2	64.9	62.8	60.7	58.7	56.8	55	53.3
Strength	70	10	**# Accepted**		78	61	35	20	5	1	0	0	0	0	0
			# Rejected		22	17	26	15	15	4	1	0	0	0	0
			# Sampled		4	5.38	6.98	9.74	16.3	21.4	13	0	0	0	0
Spray	98.17	98.17	**Mean**	76.57	73.73	70.98	68.42	65.97	63.71	61.65	59.59	57.63	55.76	53.99	52.32
Rating (UL)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Rejected	100	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	9	9	9	9	9	9	9	9	9	9	9	9
Water (UL)	13.7	13.7	**Mean**	16.71	17.11	17.49	17.85	18.19	18.51	18.8	19.08	19.36	19.62	19.87	20.1
Adsorption	20 (max)	9.55	**# Accepted**												
			# Rejected												
			# Sampled												
Chem (UL)	2.32	2.32	**Mean**	1.81	1.742	1.677	2.32	1.559	1.506	1.457	1.408	1.362	1.318	1.276	1.237
Adsorption	1.3	0.29	**# Accepted**	99	96	92	89	82	74	60	46	27	16	2	0
			# Rejected	1	3	4	3	7	8	14	14	19	11	14	2
			# Sampled	4	4.36	4.82	5.2	5.72	6.41	8.05	11.78	16.41	20.81	20.44	17

Bayesian Sample Plan, Weibull (.03,.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.679	0.654	0.632	0.613	0.595	0.578	0.563	0.549	0.536	0.523	0.511	0.5
Break	246	246	**Mean**	167	160.9	155.5	150.8	146.4	142.2	138.5	135.1	131.9	128.7	125.7	123
Strength (W)	190	27.22	**# Accepted**	2	0	0	0	0	0	0	0	0	0	0	0
			# Rejected	98	2	0	0	0	0	0	0	0	0	0	0
			# Sampled	6	8	0	0	0	0	0	0	0	0	0	0
Break	159.17	159.17	**Mean**	108.1	104.1	100.6	97.57	94.71	92	89.61	87.38	85.32	83.25	81.34	79.59
Strength (F)	115	9.73	**# Accepted**	3	0	0	0	0	0	0	0	0	0	0	0
			# Rejected	97	3	0	0	0	0	0	0	0	0	0	0
			# Sampled	4	7	0	0	0	0	0	0	0	0	0	0
Tear	10.5	10.5	**Mean**	7.13	6.867	6.636	6.437	6.248	6.069	5.912	5.765	5.628	5.492	5.366	5.25
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Rejected	100	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	15	0	0	0	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	5.093	4.905	4.74	4.598	4.463	4.335	4.223	4.118	4.02	3.923	3.833	3.75
Strength (F)	7	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Rejected	100	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	15	0	0	0	0	0	0	0	0	0	0	0
Seam	100	100	**Mean**	67.9	65.4	63.2	61.3	59.5	57.8	56.3	54.9	53.6	52.3	51.1	50
Strength	70	10	**# Accepted**	24	4	0	0	0	0	0	0	0	0	0	0
			# Rejected	76	20	4	0	0	0	0	0	0	0	0	0
			# Sampled	4	6.75	12	0	0	0	0	0	0	0	0	0
Spray	98.17	98.17	**Mean**	66.66	64.2	62.04	60.18	58.41	56.74	55.27	53.9	52.62	51.34	50.16	49.09
Rating (UL)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Rejected	100	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	9	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	13.7	13.7	**Mean**	18.1	18.44	18.74	19	19.25	19.48	19.69	19.88	20.06	20.23	20.4	20.55
Adsorption	20 (max)	9.55	**# Accepted**												
			# Rejected												
			# Sampled												
Chem (UL)	2.32	2.32	**Mean**	1.575	1.517	1.466	2.32	1.38	1.341	1.306	1.274	1.244	1.213	1.186	1.16
Adsorption	1.3	0.29	**# Accepted**	86	73	60	52	41	29	16	7	4	0	0	0
			# Rejected	14	13	13	8	11	12	13	9	3	4	0	0
			# Sampled	4	5.12	6.67	7.82	10.87	19.51	23.45	27.56	31.86	39.75	0	0

Bayesian Sample Plan, Weibull (.05,2.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.969	0.952	0.93	0.904	0.873	0.838	0.799	0.757	0.711	0.664	0.614	0.564
Break	246	246	**Mean**	238.4	234.2	228.8	222.4	214.8	206.1	196.6	186.2	174.9	163.3	151	138.7
Strength (W)	190	27.22	**# Accepted**	100	96	96	92	86	72	41	10	0	0	0	0
			# Rejected	0	4	0	4	6	14	31	31	10	0	0	0
			# Sampled	6	4.48	5.03	5.1	5.57	6.24	8.35	13.05	15	0	0	0
Break	159.17	159.17	**Mean**	154.2	151.5	148	143.9	139	133.4	127.2	120.5	113.2	105.7	97.73	89.77
Strength (F)	115	9.73	**# Accepted**	100	100	100	100	100	100	96	70	22	0	0	0
			# Rejected	0	0	0	0	0	0	4	26	48	22	0	0
			# Sampled	4	4	4	4	4	4.06	4.32	4.86	5.86	7.91	0	0
Tear	10.5	10.5	**Mean**	10.17	9.996	9.765	9.492	9.167	8.799	8.39	7.949	7.466	6.972	6.447	5.922
Strength (W)	10	1.342	**# Accepted**	89	68	21	8	1	0	0	0	0	0	0	0
			# Rejected	11	21	47	13	7	1	0	0	0	0	0	0
			# Sampled	15	20.6	31.28	28.38	28.5	30	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	7.268	7.14	6.975	6.78	6.548	6.285	5.993	5.678	5.333	4.98	4.605	4.23
Strength (F)	7	1.342	**# Accepted**	91	84	39	25	10	3	0	0	0	0	0	0
			# Rejected	9	7	45	14	15	7	3	0	0	0	0	0
			# Sampled	15	20.51	31.37	29.05	30.56	30.4	28.33	0	0	0	0	0
Seam	100	100	**Mean**	96.9	95.2	93	90.4	87.3	83.8	79.9	75.7	71.1	66.4	61.4	56.4
Strength	70	10	**# Accepted**	100	100	100	100	100	95	89	69	35	5	0	0
			# Rejected	0	0	0	0	0	5	6	20	34	30	5	0
			# Sampled	4	4.12	4.18	4.17	4.34	4.61	5.04	5.54	6.97	12.51	25.4	0
Spray	98.17	98.17	**Mean**	95.13	93.46	91.3	88.75	85.7	82.27	78.44	74.31	69.8	65.18	60.28	55.37
Rating (UL)	90	8.68	**# Accepted**	99	92	79	22	5	0	0	0	0	0	0	0
			# Rejected	1	7	13	57	17	5	0	0	0	0	0	0
			# Sampled	9	12	15.71	30.47	31.41	40	0	0	0	0	0	0
Water (UL)	13.7	13.7	**Mean**	14.12	14.36	14.66	15.02	15.44	15.92	16.45	17.03	17.66	18.3	18.99	19.67
Adsorption	20 (max)	9.55	**# Accepted**												
			# Rejected												
			# Sampled												
Chem (UL)	2.32	2.32	**Mean**	2.248	2.209	2.158	2.32	2.025	1.944	1.854	1.756	1.65	1.54	1.424	1.308
Adsorption	1.3	0.29	**# Accepted**	100	100	100	100	100	100	100	99	95	86	51	19
			# Rejected	0	0	0	0	0	0	0	1	4	9	35	32
			# Sampled	4	4	4	4.02	4.04	4.07	4.11	4.32	4.68	5.26	10.49	19.2

Truncated Sequential Sample Plan II, Weibull (.065,15)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	1	1	1	1	1	0.998	0.993	0.976	0.923	0.784	0.505	0.165
Break	246	246	**Mean**	246	246	246	246	246	245.5	244.3	240.1	227.1	192.9	124.2	40.59
Strength (W)	190	27.22	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	941	6	0	0
			# Sampled	26.9	26.9	27.28	27.41	27.82	28.7	29.68	31.86	27.41	8.737	3.54	0
Break	159.17	159.17	**Mean**	159.2	159.2	159.2	159.2	159.2	158.9	158.1	155.3	146.9	124.8	80.38	26.26
Strength (F)	115	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0	0
Tear	10.5	10.5	**Mean**	10.5	10.5	10.5	10.5	10.5	10.48	10.43	10.25	9.692	8.232	5.303	1.733
Strength (W)	10	1.342	**# Accepted**	881	889	891	890	882	870	814	543	8	0	0	0
Tear	7.5	7.5	**Mean**	7.5	7.5	7.5	7.5	7.5	7.485	7.448	7.32	6.923	5.88	3.788	1.238
Strength (F)	7	1.342	**# Accepted**	882	880	885	895	890	874	837	673	97	0	0	0
Seam	100	100	**Mean**	100	100	100	100	100	99.8	99.3	97.6	92.3	78.4	50.5	16.5
Strength	70	10	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	999	37	0	0
Spray	98.17	98.17	**Mean**	98.17	98.17	98.17	98.17	98.17	97.97	97.48	95.81	90.61	76.97	49.58	16.2
Rating (UL)	90	8.68	**# Accepted**	989	995	994	993	996	990	982	885	14	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	13.7	13.7	13.7	13.7	13.7	13.73	13.8	14.03	14.75	16.66	20.48	25.14
Adsorption	20	9.55	**# Accepted**	963	953	961	966	963	953	965	972	905	589	337	172
Chem(UL)	2.32	2.32	**Mean**	2.32	2.32	2.32	2.32	2.32	2.315	2.304	2.264	2.141	1.819	1.172	0.383
Adsorption	1.3	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	557	0	0

Truncated Sequential Sample Plan II, Weibull (.07, 7)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Break	246	246	**Mean**	245.8	245.5	244.3	241.8	236.4	226.6	209.6	183	146.6	103.3	60.27	27.06
Strength (W)	190	27.22	**# Accepted**	1000	1000	1000	1000	1000	952	117	1	0	0	0	0
			# Sampled	27.09	27.49	28.67	29.37	30.19	26.35	13.93	7.067	4.41	3.12	2.44	2.08
Break	159.17	159.17	**Mean**	159	158.9	158.1	156.5	153	146.6	135.6	118.4	94.87	66.85	39	17.51
Strength (F)	115	9.73	**# Accepted**	1000	1000	1000	1000	1000	1000	264	0	0	0	0	0
Tear	10.5	10.5	**Mean**	10.49	10.48	10.43	10.32	10.09	9.671	8.946	7.812	6.258	4.41	2.573	1.155
Strength (W)	10	1.342	**# Accepted**	864	878	796	676	299	21	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	7.493	7.485	7.448	7.373	7.208	6.908	6.39	5.58	4.47	3.15	1.838	0.825
Strength (F)	7	1.342	**# Accepted**	858	871	828	748	507	100	0	0	0	0	0	0
Seam	100	100	**Mean**	99.9	99.8	99.3	98.3	96.1	92.1	85.2	74.4	59.6	42	24.5	11
Strength	70	10	**# Accepted**	1000	1000	1000	1000	1000	1000	514	5	0	0	0	0
Spray	98.17	98.17	**Mean**	98.07	97.97	97.48	96.5	94.34	90.41	83.64	73.04	58.51	41.23	24.05	10.8
Rating (UL)	90	8.68	**# Accepted**	991	988	988	940	596	26	0	0	0	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	13.71	13.73	13.8	13.93	14.23	14.78	15.73	17.21	19.23	21.65	24.04	25.89
Adsorption	20	9.55	**# Accepted**	960	970	971	947	929	895	726	555	375	282	199	166
Chem(UL)	2.32	2.32	**Mean**	2.318	2.315	2.304	2.281	2.23	2.137	1.977	1.726	1.383	0.974	0.568	0.255
Adsorption	1.3	0.29	**# Accepted**	1000	1000	1000	1000	1000	1000	976	250	1	0	0	0

Truncated Sequential Sample Plan II, Weibull (.03,1.1)															
	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.883	0.859	0.836	0.812	0.789	0.766	0.744	0.723	0.701	0.68	0.66	0.64
Break	246	246	**Mean**	217.2	211.3	205.7	199.8	194.1	188.4	183	177.9	172.4	167.3	162.4	157.4
Strength (W)	190	27.22	**# Accepted**	454	121	71	26	5	1	0	0	0	0	0	0
			# Sampled	18.64	15.31	12.22	10.35	9.11	8.07	7.32	6.57	6.09	5.62	5.26	4.95
Break	159.17	159.17	**Mean**	140.5	136.7	133.1	129.2	125.6	121.9	118.4	115.1	111.6	108.2	105.1	101.9
Strength (F)	115	9.73	**# Accepted**	942	341	80	5	0	0	0	0	0	0	0	0
Tear	10.5	10.5	**Mean**	9.272	9.02	8.778	8.526	8.285	8.043	7.812	7.592	7.361	7.14	6.93	6.72
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	6.623	6.443	6.27	6.09	5.918	5.745	5.58	5.423	5.258	5.1	4.95	4.8
Strength (F)	7	1.342	**# Accepted**	8	0	0	0	0	0	0	0	0	0	0	0
Seam	100	100	**Mean**	88.3	85.9	83.6	81.2	78.9	76.6	74.4	72.3	70.1	68	66	64
Strength	70	10	**# Accepted**	924	654	302	122	36	15	2	0	0	0	0	0
Spray	98.17	98.17	**Mean**	86.68	84.33	82.07	79.71	77.46	75.2	73.04	70.98	68.82	66.76	64.79	62.83
Rating (UL)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	15.3	15.63	15.95	16.28	16.59	16.91	17.21	17.49	17.8	18.08	18.36	18.63
Adsorption	20	9.55	**# Accepted**	790	741	678	607	615	556	522	535	496	461	453	429
Chem (UL)	2.32	2.32	**Mean**	2.049	1.993	1.94	1.884	1.83	1.777	1.726	1.677	1.626	1.578	1.531	1.485
Adsorption	1.3	0.29	**# Accepted**	999	974	929	813	613	410	230	115	67	40	12	0

Truncated Sequential Sample Plan II, Weibull (.035, .8)															
	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.78	0.751	0.723	0.697	0.672	0.649	0.628	0.607	0.587	0.568	0.55	0.533
Break	246	246	**Mean**	191.9	184.7	177.9	171.5	165.3	159.7	154.5	149.3	144.4	139.7	135.3	131.1
Strength (W)	190	27.22	**# Accepted**	4	2	2	0	0	0	0	0	0	0	0	0
			# Sampled	8.76	7.4	6.6	6.07	5.53	5.14	4.77	4.53	4.34	4.15	3.95	3.79
Break	159.17	159.17	**Mean**	124.2	119.5	115.1	110.9	107	103.3	99.96	96.62	93.43	90.41	87.54	84.84
Strength (F)	115	9.73		0	0	0	0	0	0	0	0	0	0	0	0
Tear	10.5	10.5	**Mean**	8.19	7.886	7.592	7.319	7.056	6.815	6.594	6.374	6.164	5.964	5.775	5.597
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	5.85	5.633	5.423	5.228	5.04	4.868	4.71	4.553	4.403	4.26	4.125	3.998
Strength (F)	7	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Seam	100	100	**Mean**	78	75.1	72.3	69.7	67.2	64.9	62.8	60.7	58.7	56.8	55	53.3
Strength	70	10	**# Accepted**	32	3	0	0	0	0	0	0	0	0	0	0
Spray	98.17	98.17	**Mean**	76.57	73.73	70.98	68.42	65.97	63.71	61.65	59.59	57.63	55.76	53.99	52.32
Rating (UL)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	16.71	17.11	17.49	17.85	18.19	18.51	18.8	19.08	19.36	19.62	19.87	20.1
Adsorption	20	9.55	**# Accepted**	588	544	526	445	459	430	429	388	402	360	368	335
Chem (UL)	2.32	2.32	**Mean**	1.81	1.742	1.677	1.617	1.559	1.506	1.457	1.408	1.362	1.318	1.276	1.237
Adsorption	1.3	0.29	**# Accepted**	531	283	120	75	28	8	4	3	1	2	0	0

Truncated Sequential Sample Plan II, Weibull (.03,.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.679	0.654	0.632	0.613	0.595	0.578	0.563	0.549	0.536	0.523	0.511	0.5
Break	246	246	**Mean**	167	160.9	155.5	150.8	146.4	142.2	138.5	135.1	131.9	128.7	125.7	123
Strength (W)	190	27.22	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
			# Sampled	5.7	5.18	4.83	4.6	4.39	4.26	4.12	3.99	3.84	3.72	3.63	3.56
Break	159.17	159.17	**Mean**	108.1	104.1	100.6	97.57	94.71	92	89.61	87.38	85.32	83.25	81.34	79.59
Strength (F)	115	9.73	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Tear	10.5	10.5	**Mean**	7.13	6.867	6.636	6.437	6.248	6.069	5.912	5.765	5.628	5.492	5.366	5.25
Strength (W)	10	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	5.093	4.905	4.74	4.598	4.463	4.335	4.223	4.118	4.02	3.923	3.833	3.75
Strength (F)	7	1.342	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Seam	100	100	**Mean**	67.9	65.4	63.2	61.3	59.5	57.8	56.3	54.9	53.6	52.3	51.1	50
Strength	70	10	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Spray	98.17	98.17	**Mean**	66.66	64.2	62.04	60.18	58.41	56.74	55.27	53.9	52.62	51.34	50.16	49.09
Rating (UL)	90	8.68	**# Accepted**	0	0	0	0	0	0	0	0	0	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	18.1	18.44	18.74	19	19.25	19.48	19.69	19.88	20.06	20.23	20.4	20.55
Adsorption	20	9.55	**# Accepted**	451	430	418	419	378	352	370	372	357	354	341	339
Chem (UL)	2.32	2.32	**Mean**	1.575	1.517	1.466	1.422	1.38	1.341	1.306	1.274	1.244	1.213	1.186	1.16
Adsorption	1.3	0.29	**# Accepted**	37	15	10	4	0	0	0	0	0	0	0	0

Truncated Sequential Sample Plan II, Weibull (.05,2.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.969	0.952	0.93	0.904	0.873	0.838	0.799	0.757	0.711	0.664	0.614	0.564
Break	246	246	**Mean**	238.4	234.2	228.8	222.4	214.8	206.1	196.6	186.2	174.9	163.3	151	138.7
Strength (W)	190	27.22	**# Accepted**	999	1000	973	771	325	72	15	0	0	0	0	0
			# Sampled	29.15	29.03	27.07	22.72	17.31	12.52	9.59	7.57	6.35	5.33	4.59	4.03
Break	159.17	159.17	**Mean**	154.2	151.5	148	143.9	139	133.4	127.2	120.5	113.2	105.7	97.73	89.77
Strength (F)	115	9.73	**# Accepted**	1000	1000	1000	999	758	113	2	0	0	0	0	0
Tear	10.5	10.5	**Mean**	10.17	9.996	9.765	9.492	9.167	8.799	8.39	7.949	7.466	6.972	6.447	5.922
Strength (W)	10	1.342	**# Accepted**	452	183	28	3	0	0	0	0	0	0	0	0
Tear	7.5	7.5	**Mean**	7.268	7.14	6.975	6.78	6.548	6.285	5.993	5.678	5.333	4.98	4.605	4.23
Strength (F)	7	1.342	**# Accepted**	591	380	1636	46	4	0	0	0	0	0	0	0
Seam	100	100	**Mean**	96.9	95.2	93	90.4	87.3	83.8	79.9	75.7	71.1	66.4	61.4	56.4
Strength	70	10	**# Accepted**	1000	1000	1000	995	812	356	66	0	0	0	0	0
						43									
Spray	98.17	98.17	**Mean**	95.13	93.46	91.3	88.75	85.7	82.27	78.44	74.31	69.8	65.18	60.28	55.37
Rating (UL)	90	8.68	**# Accepted**	749	367	43	5	0	0	0	0	0	0	0	0
Water (UL)	13.7 (max)	13.7	**Mean**	14.12	14.36	14.66	15.02	15.44	15.92	16.45	17.03	17.66	18.3	18.99	19.67
Adsorption	20	9.55	**# Accepted**	948	925	892	841	760	693	598	556	510	449	407	405
Chem (UL)	2.32	2.32	**Mean**	2.248	2.209	2.158	2.097	2.025	1.944	1.854	1.756	1.65	1.54	1.424	1.308
Adsorption	1.3	0.29	**# Accepted**	1000	1000	1000	1000	999	935	705	329	85	13	3	0

Aggregated Sequential Sample Plan I, Weibull (.065,15)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	1	1	1	1	1	0.998	0.993	0.976	0.923	0.784	0.505	0.165
Agg Score			**# Accepted**	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	0	0
			Avg Sample	2.96	2.95	2.96	2.95	2.96	2.96	2.98	3.05	3.74	4.95	2	1

Aggregated Sample Plan I, Weibull (.07, 7)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			**Degradation**	0.999	0.998	0.993	0.983	0.961	0.921	0.852	0.744	0.596	0.42	0.245	0.11
Seq Agg			**# Accepted**	1000	1000	1000	1000	1000	1000	1000	998	4	0	0	
			Avg Sample	2.96	2.96	2.99	3.01	3.16	3.77	4.04	5	2.07	2	1.04	

Aggregated Sample Plan II, Weibull (.03,1.1)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
TEST			Degradation	0.883	0.859	0.836	0.812	0.789	0.766	0.744	0.723	0.701	0.68	0.66	0.64
Agg Seq			# Accepted	1000	1000	1000	1000	1000	1000	999	995	936	731	397	113
			Avg Sample	3.99	4.02	4.19	4.63	4.91	4.99	5	5.05	5.17	4.87	3.9	2.82

Aggregated Sample Plan I, Weibull (.035, .8)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
			Degradation	0.78	0.751	0.723	0.697	0.672	0.649	0.628	0.607	0.587	0.568	0.55	0.533
Agg Seq			# Accepted	1000	998	992	905	567	237	54	10	0	0	0	0
			Avg Sample	4.97	5	5.04	5.11	4.45	3.33	2.51	2.14	2.03	2.01	2	2

Aggregated Sample Plan I, Weibull (.03,.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
			Degradation	0.679	0.654	0.632	0.613	0.595	0.578	0.563	0.549	0.536	0.523	0.511	0.5
Agg Seq			# Accepted	693	307	69	7	3	0	0	0	0	0	0	0
			Avg Sample	4.78	3.6	2.57	2.15	2.05	2.01	2	2	2	2	2	2

Aggregated Sample Plan I, Weibull (.05,2.5)

	Min Value / Reject Value	Mean/ Std Dev		Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16
			Degradation	0.969	0.952	0.93	0.904	0.873	0.838	0.799	0.757	0.711	0.664	0.614	0.564
Agg Seq			# Accepted	1000	1000	1000	1000	1000	1000	1000	999	979	463	24	0
			Avg Sample	3.09	3.27	3.63	3.91	4	4.16	4.85	5	5.13	4.11	2.26	2

Appendix C. Original Sampling Plan with Attribute Data

In this appendix, we show the results of simulating the original sampling plan with attribute data, rather than variable data, so we could compare the results to the Bayesian methodology which also uses attribute data. If a test result was greater than the minimum requirement, it was considered a pass, and if a test result was less than the minimum requirement, it was considered a fail, just as in the Bayesian methodology. We ran the same tests as in the Bayesian methodology and we came up with the following results. The original sampling plan results, which are listed as binomial, are given along with the Bayesian results so they can be compared.

Table 18. Bayesian Plan and Original Sampling Plan with Attribute Data

PERCENTAGE OF SUITS METHODOLOGIES REJECTED, TYPE II SIMS												
METHOD	> 4 Years Early	4 Years Early	3 Years Early	2 Years Early	1 Year Early	Year Failed	1 Year Late	2 Years Late	3 Years Late	4 Years Late	> 4 Years Late	Avg # of Samples
	DEGRADATION FUNCTION 1											
BINOMIAL	4.811	1.51	1.465	1.645	2.263	6.217	27.59	43.86	10.64	0	0	360
BAYESIAN	2.86	1	1.29	1.14	1.57	2.43	18.71	26.14	43.57	1.29	0	321.47
	DEGRADATION FUNCTION 2											
BINOMIAL	0	0	1.777	1.85	2.543	4.644	12.74	23.63	20.35	27.48	4.987	360
BAYESIAN	0	0	1.71	0	2	1.43	6.43	16.71	17.29	22	30.43	233.14
	DEGRADATION FUNCTION 3											
BINOMIAL	0	0	0	0	0	57.16	10.36	8.182	9.513	6.437	8.35	360
BAYESIAN	0	0	0	0	0	30.43	0	15.29	4.29	3.86	37.14	151.26
	DEGRADATION FUNCTION 4											
BINOMIAL	0	0	0	0	0	90.02	5.95	3.228	0.75	0.055	0	360
BAYESIAN	0	0	0	0	0	53.14	10.29	9.86	8.14	4	14.57	125
	DEGRADATION FUNCTION 5											
BINOMIAL	0	0	0	0	0	99.63	0.366	0	0	0	0	360
BAYESIAN	0	0	0	0	0	83.57	5.43	2.43	1.14	1.57	5.86	176.61
	DEGRADATION FUNCTION 6											
BINOMIAL	0	0	0	0	0	11.22	16.95	16.9	11.35	7.782	35.8	360
BAYESIAN	0	0	0	0	0	3	5.57	15	12.57	6.43	54.71	185.22

Note that the Bayesian plan still does not perform as well even when compared to another methodology using attribute data. The Bayesian plan rejects less suits in the Year Failed column than does the original sampling plan when it also uses attribute data. See section 4.6 for an explanation as to why the Bayesian plan does not do so well.

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. AGENCY USE ONLY *(Leave blank)*

2. REPORT DATE
March 1996

3. REPORT TYPE AND DATES COVERED
Master's Thesis

4. TITLE AND SUBTITLE
SURVEILLANCE PLAN FOR MONITORING THE SHELF-LIFE OF CHEMICAL DEFENSE COVERALLS

5. FUNDING NUMBERS

6. AUTHOR(S)
Robert Earl Neher Jr , Captain, USAF

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Air Force Institute of Technology,
WPAFB OH 45433-7765

8. PERFORMING ORGANIZATION REPORT NUMBER
AFIT/GOR/ENY/96M-01

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
HSC/YAEC
8107 13th St.
Brooks AFB, TX 78235-5218

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

12b. DISTRIBUTION CODE
A

13. ABSTRACT *(Maximum 200 words)*

This thesis found a surveillance plan to be used to monitor the shelf-life of the Air Force's chemical defense coveralls. The sampling tests are destructive and the objective was to find a surveillance plan that would minimize the number of suits sampled yet provide enough information to accurately determine if the chemical defense coveralls had degraded past a minimum acceptable level. Six sampling plans were developed and analyzed. The sampling plans included the Air Force's original fixed sampling plan, several variations of sequential sampling plans, a Bayesian sampling plan, and an ad hoc pre-posturing plan. Each of the sampling plans were simulated under various degradation functions with various values for test variables. It was determined that the truncated sequential plan showed the most promise for accurately predicting if a population of suits should be accepted or rejected using a minimal amount of suits.

14. SUBJECT TERMS
Reliability, Bayesian, Surveillance, Sequential Sampling, Sampling, Shelf-Life

15. NUMBER OF PAGES
137

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
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